Observed Changes in Interannual Precipitation Variability in the United States

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Key Points

- We find widespread robust changes in two measures of interannual precipitation variability across the United States
- We detect increases (decreases) in annual mean precipitation and wet day frequency across the eastern (western) United States
- We explore the interaction of changes in precipitation frequency and wet day precipitation intensity on interannual variability

Abstract

Characterizing changes in precipitation patterns over time is critical for hydrologically-dependent fields like water resource management and agriculture. Here, we explore observed trends in interannual precipitation variability using a suite of metrics that describe changes in precipitation over time. We analyze daily *in-situ* Global Historical Climatology Network precipitation data from 1970 to present over seventeen internally consistent sub-national United States domains using a regional Mann-Kendall trend test. We find robustly increasing trends in annual mean precipitation and wet day frequency for most of the central and eastern U.S., but decreasing trends in the western U.S. Importantly, we identify widespread significant trends in interannual precipitation variability, with increasing variability in the southeast, decreasing variability in the far west, and mixed signals in the Rocky Mountains and north-central U.S. Our

results provide important context for water resource managers and a new observational standard for climate model performance assessments.

Plain Language Summary

While many studies have examined how annual precipitation totals and precipitation frequency have changed, few examine the variability, or consistency, of year-over-year precipitation. We test for these trends in daily observations across seventeen regions within the U.S. We find changes in yearly precipitation variability for most regions, though results in the central U.S. are mixed. We also identify rising average annual precipitation and precipitation frequency for the central and eastern U.S. and falling average annual precipitation and frequency for the western U.S. Our results are important for agriculture and water resource management and can be compared against historical climate model simulations to determine how well they reproduce observations.

Keywords

precipitation, interannual variability, precipitation variability, GHCN, NEON, NCA

Introduction

Precipitation patterns are shifting globally due to climate change (Douville et al., 2021). These changes are broadly driven by increased moisture availability due to rising temperatures (i.e., the Clausius-Clapeyron relationship) and shifts in atmospheric circulation patterns (e.g., poleward expansion of the Hadley cell; Polade et al., 2014), and are constrained by Earth's energy budget (Pendergrass and Hartmann, 2014). Observationally-based historical studies and model-based future projections of precipitation commonly characterize changes in metrics like annual mean, wet day frequency, and measures of extremes. However, determining changes in the temporal variability of precipitation is important to inform a number of societally-impactful hydrological fields.

Interannual variability of precipitation describes the degree of consistency in year-over-year precipitation totals: higher variability equates to greater irregularity of annual totals about the annual mean, which brings challenges to fields dependent on water resources. For example, greater precipitation variability reduces crop yields (Shortridge, 2019; Rowhani et al., 2011) and decreases a grazing area's ability to support livestock (Sloat et al., 2018). Hydrologically, shifts in interannual precipitation variability are altering the effectiveness of hydroelectric dams (Qin et al., 2020; Boadi & Owusu, 2019), impacting water quality via increased agricultural runoff (Loecke et al., 2017), and may also be driving increased variability in Laurentian Great Lake water levels (Gronewold et al., 2021). Despite the importance of interannual variability, summary assessments like the U.S. National Climate Assessment (NCA) have not yet included characterizations of its recent changes, instead focusing on mean and extreme precipitation

(Easterling et al., 2017). Here, to better describe historical changes in the year-over-year distribution of precipitation across the U.S., we examine shifts in observed interannual precipitation variability, as well as annual mean precipitation and wet day frequency – two metrics useful for understanding observed changes in interannual precipitation variability.

How is interannual precipitation variability projected to change?

Global climate models project that interannual precipitation variability will increase with rising greenhouse gas concentrations (Boer, 2009; Polade et al., 2014; Berg and Hall, 2015). Increases in the interannual variability of precipitation of ~4%/K are projected globally, with ~5%/K projected over land (Pendergrass et al., 2017; Wood et al., 2021; Chou and Lan, 2012), though some projections estimate smaller increases (He et al., 2018). He et al. (2018) explain that the drivers of projected changes in interannual precipitation variability vary spatially; the increase of mean state specific humidity leads to an increase in variability over areas of climatological ascent. Conversely, variability increases in areas of climatological descent are primarily driven by changes in mean state precipitation. Good et al. (2016) further tie interannual precipitation variability to wet season length, rainfall event intensity, and variability in interstorm wait times.

A number of studies have used global climate models to project changes in interannual precipitation variability over the U.S. Wood et al. (2021) and Polade (2014) both noted a slight, but widespread, increase in interannual variability over the U.S. by 2100 under the RCP8.5 emissions scenario. Similarly, Chou and Lan (2012) and Pendergrass et al. (2017) project increased interannual variability over the U.S. midwest, northeast, and northwest using A1B and RCP8.5 emissions scenarios, respectively. Regionally, Berg and Hall (2015) and Swain et al.

(2018) find increasing variability for California across multiple metrics using a suite of RCP8.5-driven CMIP5 models.

Despite numerous model projections of interannual precipitation variability change, there remains a dearth of observation-based analyses on the topic. Recently, Zhang et al. (2021) conducted a western U.S.-focused study that identified increases in precipitation variability using *in-situ* observations from 1976-2019, however, their investigation was regionally limited and quantified trends in only one precipitation variability metric, the coefficient of variation. We are aware of no other regional or whole U.S.-focused observational precipitation variability analyses. To address this deficiency in observational studies and produce an observational standard for model studies, we explore changes in interannual variability and relevant precipitation metrics throughout the U.S. using a full complement of *in-situ* measurements.

Methods

To characterize interannual precipitation variability in the U.S., we use daily *in-situ* station data from the Global Historical Climatology Network Daily (GHCN-D). The National Centers for Environmental Information (NCEI) curate the GHCN-D database, which includes the most complete collection of U.S. daily data available (Menne et al., 2012). GHCN-D observations have a sensitivity of 0.1 mm and are subjected to a sequence of quality control tests (Durre et al., 2010). To identify station observations with sufficient length and completeness for trend analysis, we require station records to consist of 90% or more complete station-years to qualify, where a complete station-year must contain 90% or more of all possible daily records. This filtered our set of available U.S. stations from 63,571 to 2,542 (using a 1970 start year); domain summary statistics of station availability are shown in Table S1. To overcome some of the limitations of individual station statistics, such as internal variability (e.g., Fischer et al., 2013), we center our analysis on regional trends by using domains determined by the National Ecological Observatory Network (NEON). These twenty domains were created to possess internally homogeneous climates but remain distinct across-domains, as determined by a multi-variable analysis using nine climate variables (Keller et al., 2008; Schimel et al., 2011). As labeled in Figure 1a, we use the seventeen domains that lay predominantly within the contiguous United States. We also perform our analysis for U.S. NCA regions (Easterling et al., 2017) with results included within the Supporting Information.

We employ regional Mann-Kendall trend tests to identify trends in precipitation at the NEON-domain level. Mann-Kendall trend tests are nonparametric, rank-based tests which determine if a trend exists in data regardless of underlying distribution (Mann, 1945; Kendall, 1975). They are suitable for detecting robust trends in hydrological time series (Hamed, 2008) and commonly used in studies assessing trends of precipitation over time (e.g., Zhang et al., 2021; Roque-Malo and Kumar, 2017). The regional Mann-Kendall trend test determines if a trend is present within a collection of time series by combining individual test statistics and examining the consistency in trend direction across station-specific Mann-Kendall trend tests; further description of the regional Mann-Kendall test can be found in Helsel and Frans, 2006. We apply the Trend-Free Pre-Whitened Mann-Kendall trend test (Yue et al., 2002) to account for lag-one autocorrelation present within the investigated data. We use the Theil-Sen slope estimator to determine the slope of identified trends (Sen, 1968; Theil, 1950).

We focus our analysis on four precipitation metrics: changes in interannual precipitation variability, interannual coefficient of variation (a.k.a., relative interannual variability), annual mean precipitation, and annual wet day frequency, where a wet day is defined as a station-day observing 1 mm or more of precipitation (a threshold common in precipitation analyses; e.g., Giorgi et al., 2019). Collectively, these four variables either directly characterize interannual variability, or provide crucial information to explain shifts in interannual variability.

Here, we define interannual variability as the standard deviation in annual precipitation totals over a moving 11-year window. We use an 11-year window to limit the influence of modes of interannual climate variability (e.g., ENSO), though a sensitivity analysis reveals generally stable results for five to fifteen-year moving windows (Table S2-S3). We similarly determine the coefficient of variation by dividing the aforementioned standard deviation by the mean annual precipitation over the concurrent 11-year moving window. Though not statistically independent, the coefficient of variation is often used as a measure of precipitation variability as it removes the effect of a changing mean state on precipitation variability (e.g., Giorgi et al., 2019). For example, a rise in annual mean precipitation can lead to a corresponding rise in interannual variability as a higher baseline of annual precipitation results in greater fluctuations around the baseline, even if the variations are proportionally the same. This dependency is accounted for by the coefficient of variation. For ease of understanding, we will henceforth refer to the coefficient of variation as the relative interannual variability.

In addition to performing a sensitivity analysis on the moving window width, we analyzed the stability of precipitation trends across time periods by incrementally performing calculations using starting dates every ten years from 1920 through 1980. We present findings using a 1970 starting date as it provides a balance of widespread station availability and length of observation record, but highlight discrepancies we identify within the sensitivity analysis in the discussion section. The full results of the sensitivity analysis are presented in the Supporting Information (Tables S2-S7).

Results

To properly contextualize changes in interannual variability, we must first assess changes in annual mean precipitation and precipitation frequency over our domain. We find statistically significant ($p < 0.05$) increases in annual mean precipitation for the majority of domains east of the Rocky Mountains. These increases range from 3.3-22.7 mm/decade (0.3-2.7%/decade), with larger increases for a subset of central and eastern domains ranging from 12.3-22.7 mm/decade (1.4-2.7%/decade; Figures 1a and 2, Tables S9-S10). We identify statistically significant negative trends in annual mean precipitation over the western U.S. between -14.9 to -4.7 mm/decade (-5.8 to -1.4%/decade), with annual mean precipitation increasing only in the Pacific Northwest (13.4 mm/decade, 0.9%/decade). Spatial patterns in annual wet day frequency changes largely mirror changes in annual mean precipitation, with some additional non-significant domains (Figure 1b). We observe statistically significant increases in wet day frequency for northern domains east of the Rocky Mountains, and statistically significant decreases for most western domains, as well as the Southern Plains and Southeast domains. Changes in wet day frequency range from -2.0 to 0.8 wet days/decade (-6.3 to 0.7%/decade), with the greatest increases generally located in the most northern and southern domains (Figures 1b and 2, Tables S9-S10).

Given robust trends in observed annual precipitation, it is important to determine whether such changes were equally distributed over time, or if precipitation variability has changed. Here, we identify statistically significant trends in both the interannual variability and relative interannual variability of precipitation for most domains (Figures 1c-d, 2, Tables S9-S10). Changes in interannual variability range from -10.6 to 19.9 mm/decade (-4.4 to 9.5%/decade), with changes not reaching statistical significance for five domains, predominantly in the north central U.S. Generally, interannual variability is decreasing in the western U.S. and increasing in the south central and northeastern U.S. (Figure 1c). We observe broadly similar spatial patterns in trends of relative interannual variability, although five domains switch from significant to non-significant trends or vice versa. The direction of change in the Desert Southwest domain switched from significantly negative to significantly positive (Figures 1c-d, 2); we explore this discrepancy in the discussion section. Collectively, trends in relative interannual variability range from -3.0 to 9.6%/decade with statistically significant changes occurring in all but one domain (Northeast). Results for U.S. NCA regions reveal similar spatial patterns and can be found in the Supporting Information (Figures S1-S2, Tables S11-S12).

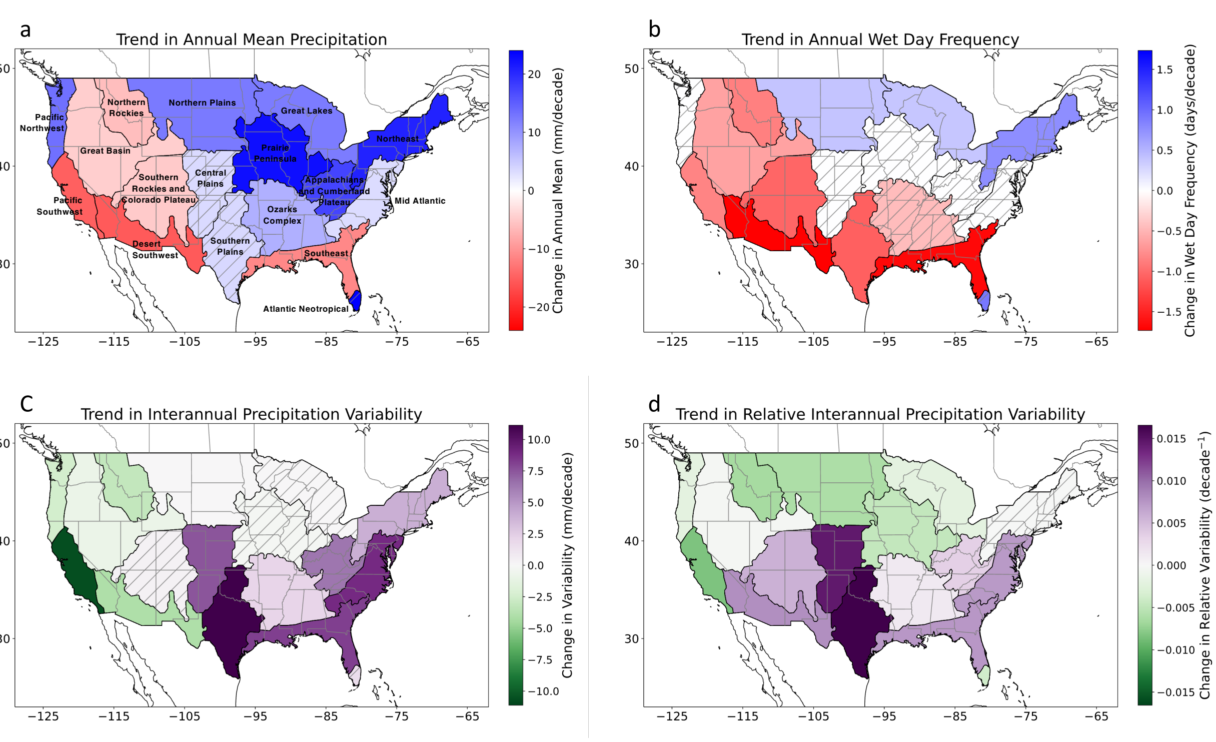

Figure 1: Domain Trends in Various Precipitation Metrics. (a) Map of changes in annual mean precipitation for each NEON domain within the contiguous U.S. Red-blue fill indicates domain-level trends in annual precipitation in mm/decade (dark grey borders). Hatching indicates domain trend is zero or does not reach statistical significance. (b) Same as (a) but for annual wet day frequency and units of days/decade. (c) Same as (a) but for interannual precipitation variability with purple-green fill and units of mm/decade. (d) Same as (c) but for relative interannual precipitation variability and units of decade^{-1}.

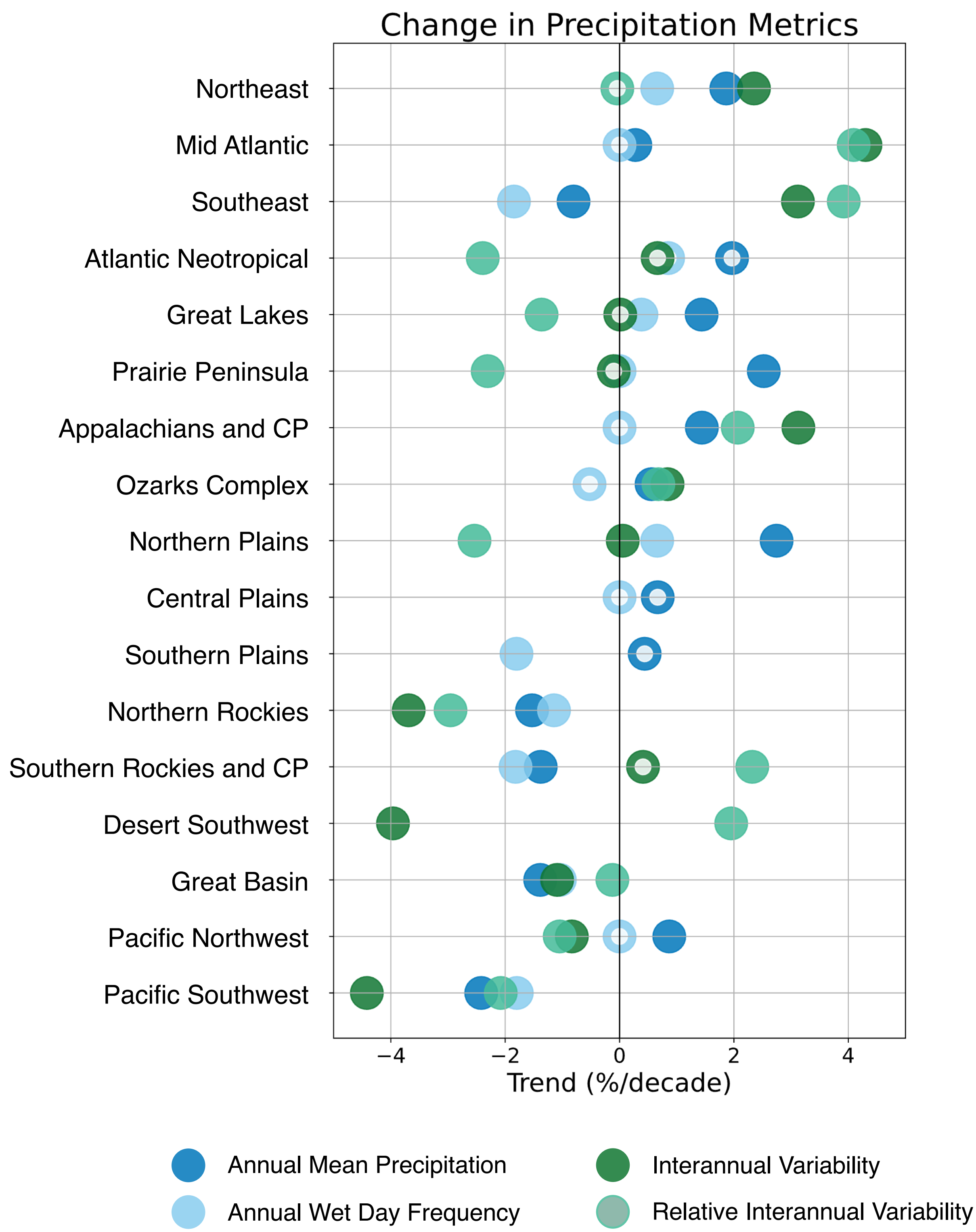

Figure 2: Domain Trends in Annual Precipitation Metrics. Trends in annual mean precipitation (dark blue), annual wet day frequency (light blue), interannual precipitation variability (dark green), and

relative interannual precipitation variability (light green) for each domain. Trends are normalized against the mean value within each domain to produce trends in percent change/decade. Non-filled circles indicate non-significant domain-trends ($p > 0.05$). Note that outlying trends in both metrics of interannual variability for the Central and Southern Plains, as well as annual mean precipitation and annual wet day frequency in the Desert Southwest, are not displayed.

Discussion

Broadly, our analysis of precipitation trends in the United States reveals increasing interannual variability for the south-central and eastern U.S., decreasing interannual variability for the Pacific coast, and mixed trends in the north-central and Rocky Mountain portions of the U.S., depending on the variability metric of interest. These changes are side-by-side with generally rising annual mean precipitation and wet day frequency over the central and eastern United States, and generally falling trends in the western United States.

One result of particular interest is the finding that in the Desert Southwest interannual variability *decreased* but relative interannual variability *increased* at a statistically significant level. In addition, the magnitude of trends in variability differed across metrics by one percent or more for ten domains. We explain this between-metric discrepancy with an examination of the components which influence interannual variability.

`Together, changes in frequency and daily precipitation intensity drive changes in interannual and relative interannual precipitation variability. We demonstrate the interplay between these four metrics with the theoretical example in Figure 3, which depicts the differential and combined effects of: a 10% increase in precipitation frequency (Figure 3a-c), a 10% increase in wet day intensity (Figure 3d-f), and both simultaneously (Figure 3g-i). In these examples, when intensity increases, it does so uniformly across the underlying precipitation distribution (i.e., not driven solely by intensity increases in extreme events).

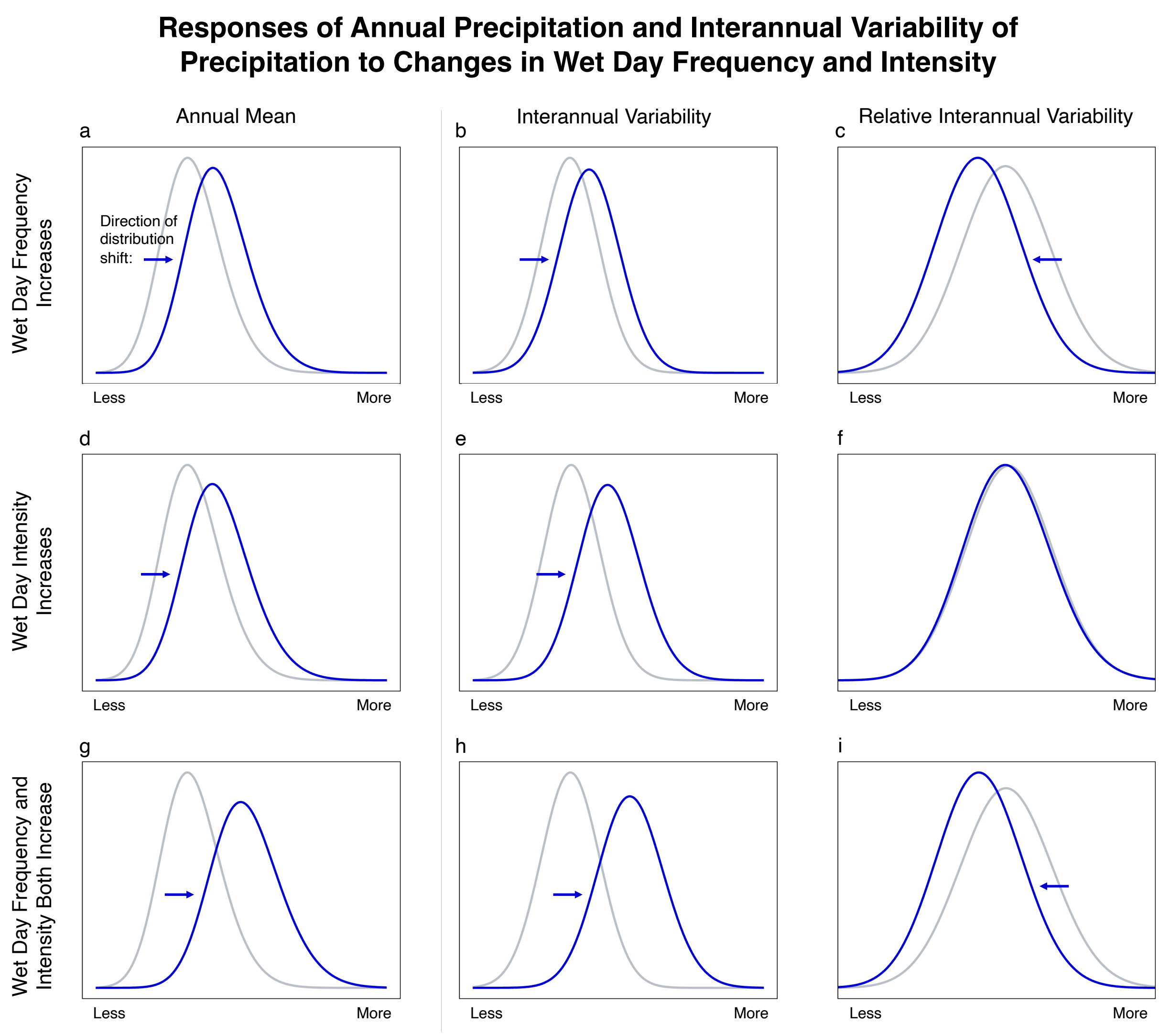

Figure 3: Responses of Annual Precipitation Totals and Interannual Variability of Precipitation to Changes in Wet Day Frequency and Intensity. (a) Initial probability distribution function (light grey) of

annual precipitation totals based on Great Lakes domain precipitation intensity distribution. Projected probability distribution function (blue) after incorporating 10% increase in wet day frequency. (b) Same as (a) but for interannual variability of precipitation. (c) Same as (a) but for relative interannual variability of precipitation. (d-f) Same as (a-c) but projected probability distribution function incorporates a 10% increase in mean wet day intensity while the standard deviation of precipitation intensity distribution remains the same. (g-i) Same as (a-c) but projected distribution function incorporates a 10% increase in both wet day frequency and mean wet day intensity.

Holding intensity constant, an increase solely in wet day frequency leads to an increase in interannual variability but a *decrease* in relative interannual variability (Figures 3b-c). As would be expected, an increase in wet day frequency produces an increase in annual precipitation totals (Figure 3a). This rise in mean state leads to a corresponding proportional increase in interannual variability as larger annual totals provide a greater baseline for interannual fluctuations. However, after accounting for the shift in baseline, *relative* interannual variability decreases. As wet day frequency rises, the contribution of extreme events toward annual totals is reduced, along with the likelihood that a given year of precipitation will be unduly influenced by extreme outlier events. Consequently, year-over-year annual precipitation totals become more consistent with more frequent precipitation. This scenario can be seen in reverse for the Desert Southwest domain: interannual variability decreases and relative interannual variability increases despite no shift in underlying precipitation intensities for the Desert Southwest (Harp and Horton, 2022).

The impacts of shifts in wet day precipitation intensity on the two metrics of interannual variability are more nuanced. Generally, increases in mean wet day precipitation intensity will lead to increases in interannual variability, however, the standard deviation of the underlying wet day precipitation intensity distribution has critical impacts on relative interannual variability. For example, if the standard deviation of wet day precipitation intensity does not change, then an increase in the mean wet day precipitation intensity leads to negligible impacts on relative interannual variability (Figure 3f). This is the case for the observed changes over the Northeast domain. Here, both wet day frequency and intensity increase (Harp and Horton, 2022), leading to a 2.4% rise in interannual variability but a negligible change in relative interannual variability. Stepping back, an increase in the standard deviation of wet day intensity leads to an increase in relative interannual variability and vice versa. These intricacies are illustrated in Figures S3-S4: Figure S3 shows an increase in standard deviation driven by changes at high intensities and Figure S4 shows an increase in standard deviation driven by changes at lower-to-moderate intensities. Ultimately, changing interannual variability is a byproduct of changes in wet day frequency and the underlying precipitation intensity distribution – both the change in mean and standard deviation of the intensity distribution are important – which can combine to produce differential impacts on interannual variability and relative interannual variability.

A second potential path toward changes in interannual precipitation variability involves shifting of relevant modes of climate variability themselves. This is the case in the broader southeastern U.S. where we find increasing interannual variability in both metrics; a shift which has previously been linked to changes in the intensity and location of the western ridge of the

North Atlantic Subtropical High (a.k.a. the Bermuda High; Cherchi et al., 2018; Li et al., 2010; Bishop et al., 2019). More specifically, this change in regional climate dynamics in part explains how the Central and Southern Plains have the most substantial changes in both interannual variability (6.2% and 9.5%, respectively) and relative interannual variability (6.1% and 9.6%, respectively) despite modest shifts in annual precipitation and wet day frequency. An additional factor driving these regional changes is a strengthening of the underlying precipitation intensity distribution, with increases in mean wet day intensity of 4.6% and 8%, respectively (Harp and Horton, 2022). We also highlight results for the broader southwestern U.S. (Pacific Southwest, Desert Southwest, Southern Rockies and Colorado Plateau, and Great Basin NEON domains), portions of which have recently experienced the greatest soil moisture deficit in over 1,000 years (Williams et al., 2022). Over the past ~50 years, we find decreasing trends in annual mean precipitation, wet day frequency, and interannual precipitation variability, with mixed trends in relative interannual precipitation variability over this region (Figure 1). Underlying drivers of both observed and projected future changes in precipitation in this region remain an area of active investigation, with a cohesive picture yet to emerge (e.g., Seager et al. 2015; Swain et al., 2018).

Comparison with earlier literature

Our results on changes in observed annual mean precipitation largely mirror earlier findings from the fourth National Climate Assessment (Easterling et al., 2017) with subtle differences over the south-central and northwestern U.S. Additionally, we find similar trends in wet day frequency as earlier *in-situ*, station-based observational studies such as Pal et al. (2013), though there is a discrepancy in findings over the mountain west and a central band across the eastern U.S. Despite a similar observation-driven and interannual variability-focused methodology, we identify differences between our findings and those of Zhang et al. (2021), which looked at a subset of our domain of interest (the western U.S.). Specifically, within the overlapping domains in our studies, we find statistically significant changes in relative interannual variability for all domains, while Zhang et al. find statistically significant changes in just three domains. The signs of the identified trends for these three domains do, however, agree with our results. We similarly find significant results across more domains for annual mean precipitation and wet day frequency than Zhang et al., though the signs of trends nearly perfectly overlap across all three precipitation metrics. These discrepancies may be a byproduct of methodological decisions. For example, despite also using GHCN-D data, Zhang et al. focus their analysis on the period from 1976-2019 and use a shorter moving window (five years) for calculation of relative interannual variability, though our sensitivity analysis did not reveal strong window width dependency (Tables S2-S7).

While an imperfect comparison, we also compare our results of observed interannual variability with a suite of studies using high emission scenario model projections to determine if trends emerging in historical observations mirror future estimates. Our findings of increasing interannual variability of precipitation in the midwest and northeast match those of Chou and Lan (2012) and Pendergrass et al. (2017), though we disagree over the sign of change in the northwest U.S. Both Chou and Lan (2012) and Pendergrass et al. (2017) attribute rising interannual precipitation variability to greater moisture availability connected with increasing temperatures. The spatial patterns in interannual variability shifts we identify also differ from the generally uniform nationwide-increases projected by Wood et al. (2021) and Polade (2014), particularly in the western U.S. Similarly, our findings of falling interannual variability in California disagree with modeled increases presented in Berg and Hall (2015) and Swain et al. (2018), though neither study predicts an emergence of signal until the mid-21st century. Lastly, it should be noted that while our study examines changes in interannual variability over a period of rapidly increasing greenhouse gas concentrations and subsequent climate impacts, unlike the above studies, we do not explicitly examine the effects of climate change on interannual variability.

Limitations and Sensitivity Analysis Implications

There are potential limitations of our study, beginning with an underlying assumption that stations within NEON domains are sufficiently homogeneous. While NEON domains were created to possess internally consistent climates, within-domain variability may exist and inconsistent station availability may influence domain-level findings. The quantity of qualifying stations also varies between domains and can impact the reliability of results; this is especially true for the Atlantic Neotropical domain with only six qualifying stations. Our sensitivity analysis revealed two domain clusters with start year-dependent results, in agreement with Kunkel (2003), which describes the importance of length of record for analysis, and notes that shorter time series may exhibit different trends than those from a greater length of record for the same location. First, the direction of relative interannual variability trends switches over four central domains between a 1950 and 1960 start date. Similarly, results for the western U.S. show a distinct shift in precipitation trends between a 1950 or earlier start date and a 1960 or

1970 start date. This shift occurs in trends for all metrics and across at least half of the western NEON domains (Tables S2-S6). Thus, while we have focused on results using a 1970 start date and 11-year moving window, we note that this combination should not be considered definitive and as such include results of analyses based on a 1950 start date in the Supporting Information (Figures S5-S8, Tables S13-S16). We used the Trend-Free Pre-Whitened Mann-Kendall test for this analysis. While this limits the effects of short-term autocorrelation, it does not address longer-term persistence caused by decadal or multi-decadal climate variability, such as the Pacific Decadal Oscillation, which may influence our findings (Kumar et al., 2013; Su et al., 2013).

Finally, we emphasize that although we examine trends in precipitation through a period of time of increasing greenhouse gas emissions and resultant climate impacts, we do not attempt to formally attribute changes to anthropogenic forcings. Indeed, attribution with observations alone ranges from challenging to impossible (NASEM, 2016). Observed records undersample the full distribution of potential underlying climatic states and may contain statistically significant but anthropogenically unforced trends (Lehner & Deser, 2023). To avoid such pitfalls and increase confidence, attribution analyses using single or even multi-model initial condition perturbation ensembles are recommended (Diffenbaugh et al., 2020; Deser et al., 2020).

Conclusion

We use curated daily *in-situ* precipitation measurements from the GHCN to examine domain-level trends in annual precipitation metrics, with a focus on interannual variability. We identify rises in annual mean precipitation in the central and eastern U.S. and declines in the western U.S. Trends in wet day frequency broadly mirror those of annual mean precipitation. We also reveal significant trends in interannual precipitation variability and relative precipitation variability across the U.S., though with some differences in within-domain trends depending on the variability metric of interest. Broadly, we find an increase in precipitation variability across both metrics for the southeastern U.S., a decrease along the west coast, and mixed signals in the central U.S. These findings have important implications for understanding the impact of changing precipitation variability on agriculture and water resource planning. The full complement of our results can be compared against historical climate model projections to inform climate model analyses across the full spectrum of precipitation metrics. Finally, we recommend that future studies carefully consider how interannual precipitation variability is characterized (i.e., interannual variability vs relative interannual variability) and any subsequent implications.

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Open Research and Availability Statement

The NCEI hosts publicly available GHCN-D data at https://www.ncei.noaa.gov/products/land-based-station/global-historical-climatology-network-daily. Code developed by the authors to conduct the data analysis and visualization within this study is available are publicly available and preserved at doi:/10.5281/zenodo.8065611 and developed openly at https://github.com/ryandharp/Observed_Changes_in_Interannual_Precipitation_Variability_in_the_United_States.

References

Berg, N., & Hall, A. (2015). Increased interannual precipitation extremes over California under climate change. Journal of Climate, 28(16), 6324-6334.

Bishop, D. A., Williams, A. P., & Seager, R. (2019). Increased fall precipitation in the southeastern United States driven by higher-intensity, frontal precipitation. Geophysical Research Letters, 46(14), 8300-8309.

Boadi, S. A., & Owusu, K. (2019). Impact of climate change and variability on hydropower in Ghana. African Geographical Review, 38(1), 19-31.

Boer, G. J. (2009). Changes in interannual variability and decadal potential predictability under global warming. Journal of Climate, 22(11), 3098-3109.

Cherchi, A., Ambrizzi, T., Behera, S., Freitas, A. C. V., Morioka, Y., & Zhou, T. (2018). The response of subtropical highs to climate change. Current Climate Change Reports, 4, 371-382.

Chou, C., & Lan, C. W. (2012). Changes in the annual range of precipitation under global warming. Journal of Climate, 25(1), 222-235.

Deser, C., Lehner, F., Rodgers, K. B., Ault, T., Delworth, T. L., DiNezio, P. N., Fiore, A., Frankignoul, C., Horton, D. E., Kay, J. E., Knutti, R., Lovenduski, N. S., Marotzke, J., McKinnon, K. A., Minobe, S., Randerson, J., Screen, J. A., Simpson, I. R., & Ting, M. (2020). Insights from Earth system model initial-condition large ensembles and future prospects. Nature Climate Change, 10(4), 277-286.

Douville, H., Raghavan, K., Renwick, J., Allan, R. P., Arias, P. A., Barlow, M., Cerezo-Mota, R., Cherchi, A., Gan, T. Y., Gergis, J., Jiang, D., Khan, A., Pokam Mba, W., Rosenfeld, D., Tierney, J., & Zolina, O. (2021): Water Cycle Changes. In Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change.

Diffenbaugh, N. S., Singh, D., Mankin, J. S., Horton, D. E., Swain, D. L., Touma, D., Charland, A., Liu, Y., Haugen, M., Tsiang, M., & Rajaratnam, B. (2017). Quantifying the influence of global warming on unprecedented extreme climate events. Proceedings of the National Academy of Sciences, 114(19), 4881-4886.

Durre, I., Menne, M. J., Gleason, B. E., Houston, T. G., & Vose, R. S. (2010). Comprehensive automated quality assurance of daily surface observations. Journal of Applied Meteorology and Climatology, 49(8), 1615-1633.

Easterling, D. R., Kunkel, K. E., Arnold, J. R., Knutson, T., LeGrande, A. N., Leung, L. R., Vose, R. S., Waliser, D. E., & Wehner, M. F. (2017): Precipitation change in the United States. In: Climate Science Special Report: Fourth National Climate Assessment, Volume I.

Fischer, E. M., Beyerle, U., & Knutti, R. (2013). Robust spatially aggregated projections of climate extremes. Nature Climate Change, 3(12), 1033-1038.

Giorgi, F., Raffaele, F., & Coppola, E. (2019). The response of precipitation characteristics to global warming from climate projections. Earth System Dynamics, 10(1), 73-89.

Good, S. P., Guan, K., & Caylor, K. K. (2016). Global patterns of the contributions of storm frequency, intensity, and seasonality to interannual variability of precipitation. Journal of Climate, 29(1), 3-15.

Gronewold, A. D., Do, H. X., Mei, Y., & Stow, C. A. (2021). A tug-of-war within the hydrologic cycle of a continental freshwater basin. Geophysical Research Letters, 48(4), e2020GL090374.

Hamed, K. H. (2008). Trend detection in hydrologic data: the Mann–Kendall trend test under the scaling hypothesis. Journal of hydrology, 349(3-4), 350-363.

Harp, R. D., & Horton, D. E. (2022). Observed Changes in Daily Precipitation Intensity in the United States. Geophysical Research Letters, 49(19), e2022GL099955.

He, C., Wang, Y., & Li, T. (2019). Weakened impact of the developing El Niño on tropical Indian Ocean climate variability under global warming. Journal of Climate, 32(21), 7265-7279.

Helsel, D. R., & Frans, L. M. (2006). Regional Kendall test for trend. Environmental science & technology, 40(13), 4066-4073.

Keller, M., Schimel, D. S., Hargrove, W. W., & Hoffman, F. M. (2008). A continental strategy for the National Ecological Observatory Network. The Ecological Society of America: 282-284.

Kendall, M. G. (1948). Rank correlation methods.

Kumar, S., Merwade, V., Kinter III, J. L., & Niyogi, D. (2013). Evaluation of temperature and precipitation trends and long-term persistence in CMIP5 twentieth-century climate simulations. Journal of Climate, 26(12), 4168-4185.

Kunkel, K. E., Easterling, D. R., Redmond, K., & Hubbard, K. (2003). Temporal variations of extreme precipitation events in the United States: 1895–2000. Geophysical research letters, 30(17).

Lehner, F., & Deser, C. (2023). Origin, importance, and predictive limits of internal climate variability. Environmental Research: Climate.

Li, W., Li, L., Fu, R., Deng, Y., & Wang, H. (2011). Changes to the North Atlantic subtropical high and its role in the intensification of summer rainfall variability in the southeastern United States. Journal of Climate, 24(5), 1499-1506.

Loecke, T. D., Burgin, A. J., Riveros-Iregui, D. A., Ward, A. S., Thomas, S. A., Davis, C. A., & Clair, M. A. S. (2017). Weather whiplash in agricultural regions drives deterioration of water quality. Biogeochemistry, 133(1), 7-15.

Mann, H. B. (1945). Nonparametric tests against trend. Econometrica: Journal of the econometric society, 245-259.

Menne, M. J., Durre, I., Vose, R. S., Gleason, B. E., & Houston, T. G. (2012). An overview of the global historical climatology network-daily database. Journal of atmospheric and oceanic technology, 29(7), 897-910.

National Academies of Sciences, Engineering, and Medicine. (2016). Attribution of extreme weather events in the context of climate change. National Academies Press.

Pal, I., Anderson, B. T., Salvucci, G. D., & Gianotti, D. J. (2013). Shifting seasonality and increasing frequency of precipitation in wet and dry seasons across the US. Geophysical Research Letters, 40(15), 4030-4035.

Pendergrass, A. G., & Hartmann, D. L. (2014). The atmospheric energy constraint on global-mean precipitation change. Journal of climate, 27(2), 757-768.

Pendergrass, A. G., Knutti, R., Lehner, F., Deser, C., & Sanderson, B. M. (2017). Precipitation variability increases in a warmer climate. Scientific reports, 7(1), 1-9.

Polade, S. D., Pierce, D. W., Cayan, D. R., Gershunov, A., & Dettinger, M. D. (2014). The key role of dry days in changing regional climate and precipitation regimes. Scientific reports, 4(1), 1-8.

Qin, P., Xu, H., Liu, M., Du, L., Xiao, C., Liu, L., & Tarroja, B. (2020). Climate change impacts on Three Gorges Reservoir impoundment and hydropower generation. Journal of Hydrology, 580, 123922.

Roque-Malo, S., & Kumar, P. (2017). Patterns of change in high frequency precipitation variability over North America. Scientific reports, 7(1), 1-12.

Rowhani, P., Lobell, D. B., Linderman, M., & Ramankutty, N. (2011). Climate variability and crop production in Tanzania. Agricultural and forest meteorology, 151(4), 449-460.

Schimel, D. (2011). The era of continental-scale ecology. Frontiers in Ecology and the Environment, 9(6), 311-311.

Seager, R., Hoerling, M., Schubert, S., Wang, H., Lyon, B., Kumar, A., Nakamura, J., & Henderson, N. (2015). Causes of the 2011–14 California drought. Journal of Climate, 28(18), 6997-7024.

Sen, P. K. (1968). Estimates of the regression coefficient based on Kendall's tau. Journal of the American statistical association, 63(324), 1379-1389.

Shortridge, J. (2019). Observed trends in daily rainfall variability result in more severe climate change impacts to agriculture. Climatic Change, 157(3), 429-444.

Sloat, L. L., Gerber, J. S., Samberg, L. H., Smith, W. K., Herrero, M., Ferreira, L. G., ... & West, P. C. (2018). Increasing importance of precipitation variability on global livestock grazing lands. Nature Climate Change, 8(3), 214-218.

Su, L., Miao, C., Kong, D., Duan, Q., Lei, X., Hou, Q., & Li, H. (2018). Long-term trends in global river flow and the causal relationships between river flow and ocean signals. Journal of hydrology, 563, 818-833.

Swain, D. L., Langenbrunner, B., Neelin, J. D., & Hall, A. (2018). Increasing precipitation volatility in twenty-first-century California. Nature Climate Change, 8(5), 427-433.

Theil, H. (1950). A rank-invariant method of linear and polynomial regression analysis. Indagationes mathematicae, 12(85), 173.

Williams, A. P., Cook, B. I., & Smerdon, J. E. (2022). Rapid intensification of the emerging southwestern North American megadrought in 2020–2021. Nature Climate Change, 12(3), 232-234.

Wood, R. R., Lehner, F., Pendergrass, A. G., & Schlunegger, S. (2021). Changes in precipitation variability across time scales in multiple global climate model large ensembles. Environmental Research Letters, 16(8), 084022.

Yue, S., & Wang, C. Y. (2002). Applicability of prewhitening to eliminate the influence of serial correlation on the Mann-Kendall test. Water resources research, 38(6), 4-1.

Zhang, F., Biederman, J. A., Dannenberg, M. P., Yan, D., Reed, S. C., & Smith, W. K. (2021). Five decades of observed daily precipitation reveal longer and more variable drought events across much of the western United States. Geophysical Research Letters, 48(7), e2020GL092293.