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Title

Comment on “Five Decades of Observed Daily Precipitation Reveal Longer and More Variable Drought Events Across Much of the Western United States”

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Peer reviewed

1 **Comment on ‘Five Decades of Observed Daily**
2 **Precipitation Reveal Longer and More Variable**
3 **Drought Events Across Much of the Western United**
4 **States’**

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8 **Key Points:**

- 9 • Statistical uncertainty about trends in droughts in the southwestern US is larger
10 than reported in a recent GRL letter.

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11 Abstract

12 Changes in precipitation patterns with climate change could have important im-
13 pacts on human and natural systems. Zhang et al. (2021) report trends in daily precip-
14 itation patterns over the last five decades in the western United States, focusing on me-
15 teorological drought. They report that dry intervals (calculated at the annual or seasonal
16 level) have increased across much of the southwestern U.S., with statistical assessment
17 suggesting the results are statistically robust. However, Zhang et al. (2021) preprocess
18 their annual (or seasonal) averages to compute five-year moving window averages before
19 using established statistical techniques for trend analysis that assume independence about
20 some fixed trend. Here we show that the moving window preprocessing violates that in-
21 dependence assumption and inflates the statistical significance of their trend estimates.
22 This raises questions about the robustness of their results. We conclude by discussing
23 the difficulty of adjusting for spatial structure when assessing time trends in a regional
24 context.

25 Plain Language Summary

26 A recent paper reports trends in drought in the western United States, in partic-
27 ular increases in drought in the southwestern United States, based on changes in the lengths
28 of time intervals without precipitation. In this ‘comment’ we note that the preprocess-
29 ing approach used in the paper artificially increases the apparent statistical signal in the
30 data and caution that the evidence for the trends reported is not as strong as presented
31 in the paper. We conclude by discussing the difficulty of estimating trends in a statis-
32 tically rigorous fashion across multiple weather stations.

33 Main Text

34 Zhang et al. (2021) present results on daily precipitation patterns over the last five
35 decades in the western United States using precipitation data from GHCN weather sta-
36 tions. A key focus of their work is on meteorological drought, quantified based on time
37 intervals in which daily precipitation never exceeds three mm. They report that mean
38 and longest dry intervals (calculated at the annual or seasonal level) have increased across
39 much of the southwestern U.S. The authors use Sen’s slope (also known as the Theil-
40 Sen estimator) to quantify trends and the Mann-Kendall test to quantify statistical sig-
41 nificance.

42 A key assumption of trend analysis using Sen’s slope and the Mann-Kendall test
43 is that the observations are independent about some fixed trend (Sen, 1968). It is well-
44 known that correlation can invalidate the Mann-Kendall test, such that the distribution
45 of p-values is not uniform under the null hypothesis, with an inflated probability of de-
46 tecting a non-existent trend, and there is extensive discussion of techniques for account-
47 ing for or reducing correlation (e.g., see Hamed & Rao, 1998; Yue et al., 2002; Hamed,
48 2009).

49 We attempted to reproduce the results in Zhang et al. (2021)[Figure 3a], which presents
50 station-specific trends in mean dry interval for 1976-2019. In discussions with the au-
51 thors, we learned from them that for the trend analyses, they took yearly (or seasonal)
52 averages and then computed the mean of those values within five-year moving windows.
53 This was not described explicitly in the paper, although there are references to moving
54 windows in Zhang et al. (2021)[Section 2] and the Zhang et al. (2021)[Figure 4 caption]
55 that can be read as specifically relating to the coefficient of variation (CV) calculation.
56 The authors apparently used the standard Mann-Kendall test, as implemented in the
57 `mkttest` function from the `modifiedmk` R package (Patakamuri & O’Brien, 2021).

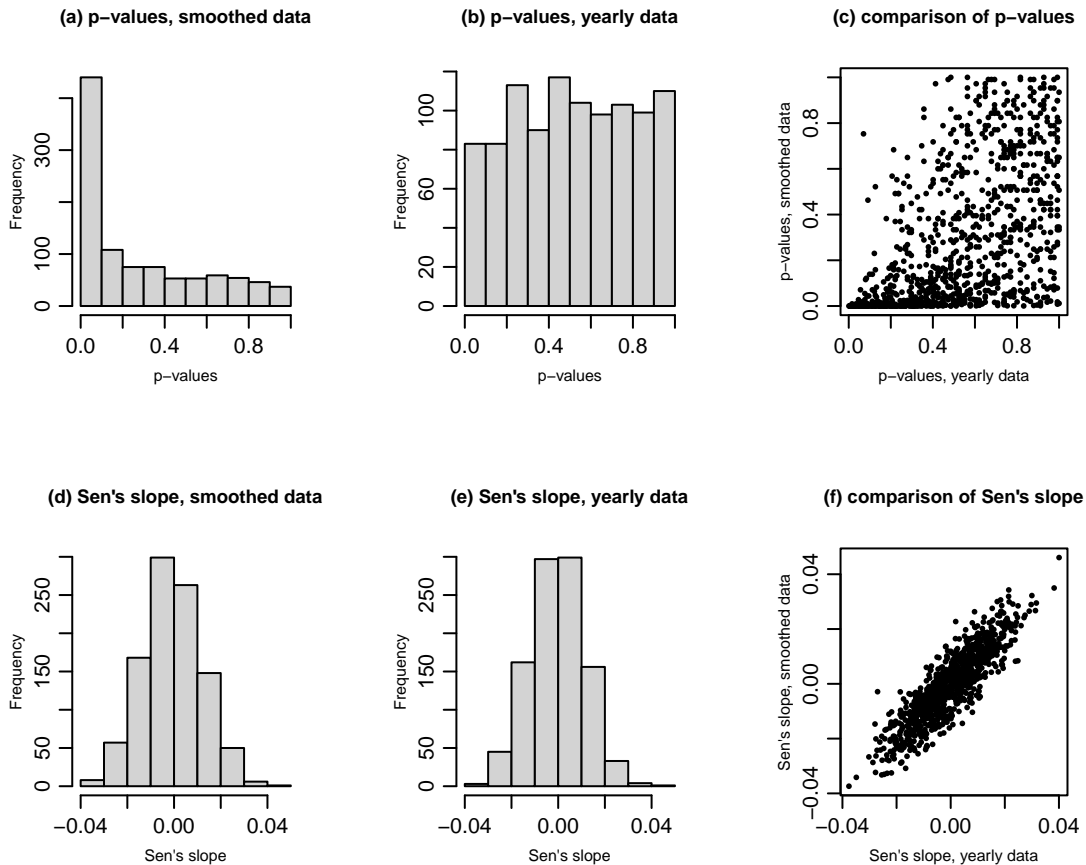


Figure 1. Comparison of p-values (top row) and Sen's slope values (bottom row) for simulated independent data and smoothed (five-year overlapping moving windows) data.

58 What is the impact of using moving averages of the observations as opposed to the
 59 observations directly? Conceptually, it's clear that using moving averages (i.e., averaging
 60 with blocks of multiple values where the blocks overlap) introduces correlation by
 61 construction. So this raises the concern that the results on statistical significance may
 62 be distorted relative to direct use of the observations (and that the Sen's slope estimates
 63 may differ as well, although the impact of correlation on the slope is less clear concep-
 64 tually).

65 We can see the impact of smoothing the raw data before trend analysis by simple
 66 simulation. We simulated 1000 'time series' of 44 'years' of completely independent data,
 67 with no trend. We then used the standard Mann-Kendall test applied to five-year mov-
 68 ing window averages, which gives 40 'years' of smoothed data. Figure 1 shows the p-values
 69 from the test and Sen's slope values with and without smoothing. It's clear that the p-
 70 values from the test when using smoothed data are not uniformly distributed and are
 71 bunched near zero compared to the uniformly-distributed p-values that we expect and
 72 see when applying the test to the unsmoothed data. Second, we note that under the null
 73 hypothesis, there does not seem to be a systematic effect on the Sen's slope values, al-
 74 though the estimates differ before and after smoothing.

75 To assess the impact of smoothing on the results of Zhang et al. (2021), we focus
76 here on Zhang et al. (2021)[Figure 3a] as an example analysis. With gracious assistance
77 from the authors regarding the details of handling missing observations and handling dry
78 intervals that overlap two (water) years, we were able to essentially reproduce the re-
79 sults of Zhang et al. (2021)[Figure 3a] (with minor quantitative differences) when using
80 five-year moving windows. Here we show the Sen’s slope values and statistical signifi-
81 cance ($p < 0.05$) when reproducing the Zhang et al. (2021) approach (Figure 2a) com-
82 pared to using the original yearly values without smoothing (Figure 2b). We see that,
83 as expected based on the simulations shown in Figure 1, the p-values are generally larger
84 when using unsmoothed data. While the trends in the Southwest (particularly Arizona,
85 southern California, and New Mexico) are generally positive, the results at many sta-
86 tions are no longer statistically significant at the 0.05 level (Figure 2b). Figure 3 shows
87 how the p-values and Sen’s slope values compare. Many of the p-values under the smoothed
88 data are bunched near zero, as also seen in the simulation. For the Sen’s slope values,
89 there seems to be a systematic pattern that the values are larger when using smoothed
90 data. This was not seen in the simulation, so it’s not clear if this is a systematic effect
91 of smoothing, but given the assumptions behind the Sen’s slope estimator, we have more
92 confidence in the slope estimates from the unsmoothed data.

93 This use of smoothing before statistical analysis of trends appears to occur through-
94 out Zhang et al. (2021). Clearly this introduces questions about the station-specific trend
95 and significance results in Zhang et al. (2021)[Figures 1 and 3] and related figures in the
96 supplemental materials. In addition, the authors report apparently similar analyses at
97 the regional level, e.g., Zhang et al. (2021)[Figures 2 and 4]. (We suspect the regional
98 analyses average over all stations in each region at the annual/seasonal level, but we are
99 not sure.) For example, Zhang et al. (2021)[Figure 4] apparently uses the five-year mov-
100 ing window averages of the mean values and five-year moving window CV values and then
101 computes Sen’s slope and uses the Mann-Kendall test to compute p-values. Of course
102 some time window is needed to compute the CV, but doing this using overlapping win-
103 dows as opposed to adjacent, non-overlapping windows introduces the same concerns about
104 inducing correlation.

105 Given the clear inflation of significance caused by smoothing, and somewhat increased
106 slope estimates, what can we conclude about the scientific results presented in Zhang
107 et al. (2021)? First, the station-specific uncertainty is clearly quite a bit larger than pre-
108 sented. This may not be surprising given we would expect a low signal to noise ratio in
109 estimating dry intervals (and related quantities) from precipitation values, which are of
110 course quite variable at the daily level. Second, in much of the western U.S. there are
111 not clear patterns in trends of mean dry interval, apart from the Southwest and possi-
112 bly the northern Great Plains (Figure 2b). The northern Great Plains show consistent
113 decreases in dry interval lengths, although only a limited number of stations are indi-
114 vidualy significant. Stations in Arizona show statistically significant increases in dry in-
115 terval lengths, but similar increases elsewhere in the Southwest are generally not signif-
116 icant.

117 To draw more robust conclusions, ideally one would adjust the p-values in light of
118 the multiple testing from doing analyses at multiple stations (e.g., the well-known false
119 discovery rate procedure of Benjamini and Hochberg (1995)), or carry out a joint sta-
120 tistical analysis of all the stations simultaneously in a way that accounts for the spatial
121 correlation structure. These are not easy tasks given the strong spatial correlation, com-
122 plicated by the real-world effects of topography and weather patterns that produce non-
123 stationary spatial correlation structure. There is consistent evidence from the multiple
124 testing literature that when there is positive correlation, if one uses adjustment proce-
125 dures such as Benjamini and Hochberg (1995) that assume independent p-values, the num-
126 ber of tests found to be significant is conservative (i.e., one should flag more tests as be-
127 ing significant than the procedure does) (Fithian & Lei, 2020). While there is statisti-

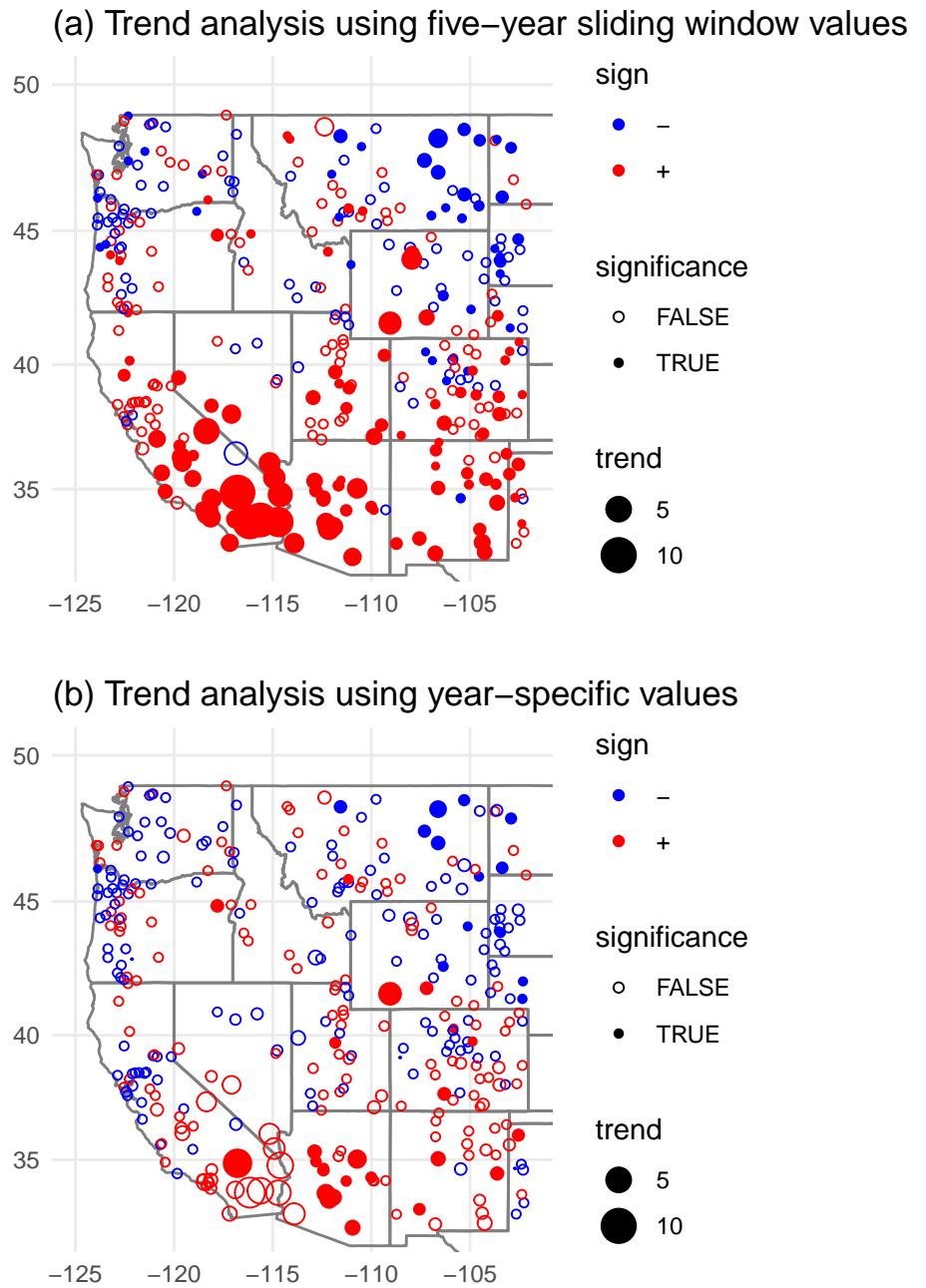


Figure 2. Trend analysis of annual mean dry interval length using Sen’s slope (days per decade) and Mann-Kendall test significance ($p < 0.05$), reproducing Zhang et al. (2021)[Figure 3a] using (a) five-year sliding window values as in Zhang et al. and (b) original year-specific values. Trends whose absolute Sen’s slope value is less than 0.5 are set to 0.5 (or -0.5 for negative trends) to avoid having points that cannot be seen.

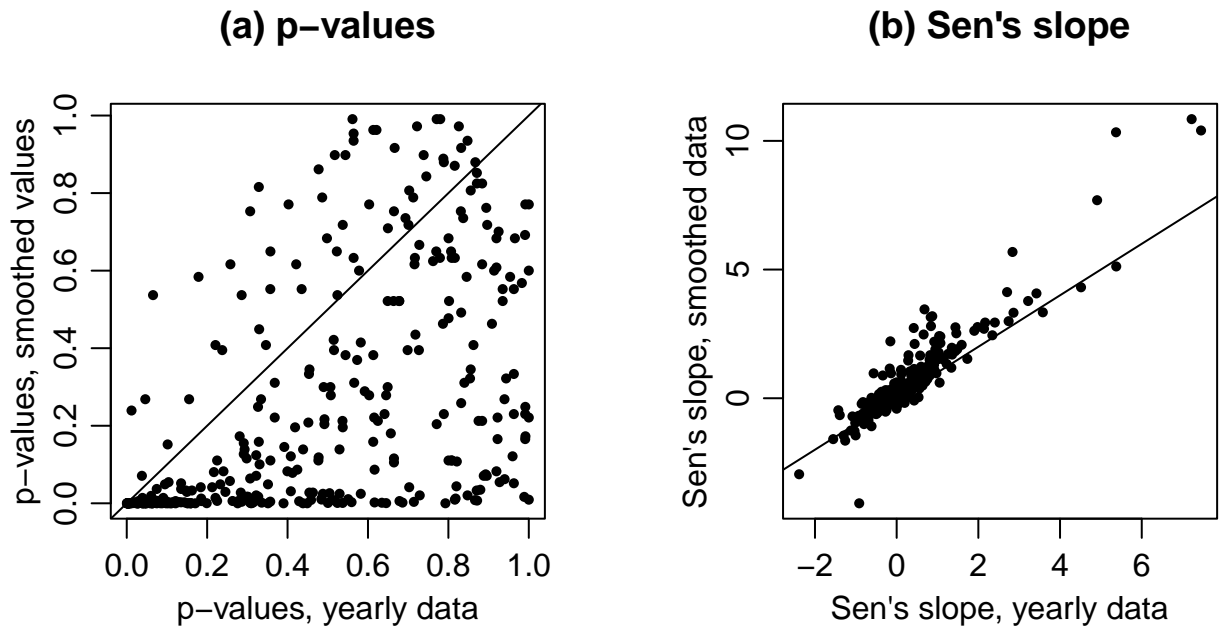


Figure 3. Comparison of (a) p-values and (b) Sen's slope values based on year-specific data and smoothed (five-year overlapping moving windows) data.

128 cal literature on spatial multiple testing (e.g., Sun et al., 2015; Risser et al., 2019), there
 129 is not a well-developed general methodology for doing so with spatially-correlated p-values.
 130 In this example, applying the Benjamini and Hochberg procedure flags no locations as
 131 significant, which is not helpful, given it is likely conservative but to an unknown degree.
 132 However, 11.5% of the locations are individually significant, greater than expected under
 133 the full null hypothesis of no trend anywhere. One could do a formal field significance
 134 test, but that would not allow us to make any formal inference about where the trends
 135 are notable. From a general perspective, the spatial clustering of the trend estimates gives
 136 some indication that there may be a more robust signal of trend in the Southwest U.S.
 137 than simply considering the raw p-values would indicate. Furthermore, such increases
 138 are consistent with future projections of decreased precipitation in the Southwest U.S.
 139 and in Mexico due to the poleward shift in the Hadley Circulation (Easterling et al., 2017)
 140 and associated changes in weather types (Prein et al., 2016). Given the limitations of
 141 p-values for making affirmative claims about hypotheses (in contrast to being able to
 142 reject a null hypothesis) (Wasserstein & Lazar, 2016), the reduced statistical significance
 143 presented here is not grounds for rejecting the hypothesis that Southwest drought is already
 144 increasing. At the same time, without a clear statistical procedure that takes account
 145 of the spatial context, it's not clear how robust the observed trends in the South-
 146 west are.

Open Research

Availability Statement

Datasets used in this study were downloaded from <https://www.ncdc.noaa.gov/ghcnd-data-access>.

Code for reproducing this analysis can be obtained from <https://github.com/paciorek/grl-comment>.

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