

1 *Technical note*

2 **Examination of Changes in Annual Maximum Gage Height in the**
3 **Continental United States Using Quantile Regression**

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22
23 Abstract

24
25 This study focuses on the detection of temporal changes in annual maximum gage height (GH)
26 across the continental United States and their relationship to changes in short- and long-term
27 precipitation. Analyses are based on 1805 U.S. Geological Survey records over the 1985-2015
28 period and are performed using quantile regression. Trends were significant only at a limited
29 number of sites, with a higher number of detections at the tails of the distribution. Overall, we
30 found only weak evidence that the annual maximum GH records have been changing over the
31 continental United States during the past 30 years, possibly due to a weak signal of change, large
32 variability, and limited record length. In addition to trend detection, we also assessed to what
33 extent these changes can be attributed to storm total rainfall and long-term precipitation. Our
34 findings indicate that temporal changes in GH maxima are largely driven by storm total rainfall
35 across large areas of the continental United States (east of the 100th meridian, U.S. West Coast).
36 Long-term precipitation accumulation, on the other hand, is a strong flood predictor in regions
37 where snowmelt is an important flood generating mechanism (e.g., northern Great Plains, Rocky
38 Mountains), and is overall a relatively less important predictor of extreme flood events.

40 1. Introduction

41 The issue of temporal changes in flooding is one that has received extensive attention in the
42 peer-reviewed literature (consult Villarini and Slater (2017) for a recent review). Changing flood
43 patterns and the existence of increasing or decreasing flood trends (both in terms of flood
44 frequency and magnitude) have important implications for the design of water-related projects
45 and flood mitigation measures, even though it is recognized that such trends cannot and should
46 not be directly extrapolated into the future. The approach most widely used to detect changes in
47 flooding resorts to: 1) the use of annual maximum discharge records, and 2) the application of
48 the Mann-Kendall test to these time series. Statements about the presence of statistically
49 significant increasing/decreasing trends are generally made as the outcome of these analyses.
50 While this traditional approach has several advantages (e.g., it is easy to perform, standardized,
51 and results can be compared across different areas), it can be complemented and improved upon
52 by working with different flood-related quantities and by using other methodologies.

53 Most of the attention in the literature has been on annual maximum discharge data. As
54 discussed in Slater et al. (2015) and Slater (2016), the use of discharge data for detecting changes
55 in flood hazard is not ideal, as high flow measurements are subject to errors associated with
56 rating curve uncertainty, and discharge trends may conceal the effect of changes in the river
57 channel capacity on the flood hazard. To address these issues, Slater and Villarini (2016)
58 recently focused on gage height (GH) rather than discharge, and showed that the changes in
59 flood risk across the continental United States were not uniform. Broadly speaking, we found
60 that large areas of the northern (southern) United States exhibited increasing (decreasing) trends
61 in the number of times that the flood thresholds established by the National Weather Service
62 (NWS), in particular for action and minor flooding, were exceeded. Working with GH time
63 series has some key advantages over discharge, since water level measurements are a more direct
64 measure of flood hazard and are less prone to errors. Yet, little is known about the trends in the
65 annual maximum GH records across the continental United States.

66 A second issue is related to the use of the Mann-Kendall test (e.g., Helsel and Hirsch 1993)
67 to identify the presence of monotonic patterns in the time series of interest. While the Mann-
68 Kendall test is perfectly appropriate, it focuses on the detection of changes in the central part of
69 the distribution of the variable of interest, and does not test for the presence of trends in different
70 parts of the distribution (e.g., in cases where the largest annual maxima are increasing while the
71 lowest annual maxima are decreasing; Kinsvater and Fried 2017). To examine the presence of
72 changes in different quantiles of the distribution, quantile regression (Koenker and Basset 1978,
73 Koenker 2005) represents a viable and well-established framework. Few studies have used
74 quantile regression in the hydrologic literature. For instance, Allamano et al. (2009) examined
75 the presence of temporal trends in the annual maximum discharge at 27 Swiss stream gages, and
76 found increasing trends, in particular for large floods. Villarini et al. (2011b) found limited
77 evidence of changes in the magnitude of flooding for the Tiber River across different quantiles
78 once step changes were accounted for. Kormos et al. (2016) found that low flow extremes
79 declined in numerous sites across the U.S. Pacific Northwest. Villarini et al. (2011a) focused on

80 annual maximum precipitation across the central United States and found that about 10% of the
81 rain gage records exhibited increasing trends, mostly for low-to-moderate quantiles (see also
82 Choi et al. (2014) for analyses focused on Wisconsin). Using quantile regression, Kim and Jain
83 (2011) found significant trends in the tail of the distribution of extreme precipitation in Korea,
84 but not in the median.

85 The literature so far has largely focused on the refinement of trend detection methods to
86 detect changes in flooding. While trend detection is useful, it remains limited if one does not
87 attempt to understand the drivers that are responsible for the observed changes (see Merz et al.
88 (2012) for a discussion). For instance, Slater and Villarini (2016) found that the frequency of
89 exceedance of the NWS flood thresholds by GH can generally be described in terms of
90 precipitation and basin wetness. Here we focus on precipitation occurring in the 10-day period
91 prior to a GH annual maximum event (“storm precipitation”) and in the 365 days prior to the
92 storm (“basin wetness”) as the key drivers of the observed changes in GH extremes, similar to
93 Slater and Villarini (2016). Moreover, we explore the dependence of these results on the
94 different quantiles of the GH distribution using quantile regression. The main contributions of
95 this work are therefore the use of GH instead of discharge, the use of quantile regression instead
96 of the more traditional Mann-Kendall test, and the attribution of the observed changes in GH to
97 storm precipitation and basin wetness.

98 The research questions we focus on in this study are:

- 99 1) What trends in GH annual maxima can we detect across the continental United States?
100 How do these results change across different quantiles of the GH distribution?
- 101 2) Do storm precipitation and basin wetness explain the changes in GH annual maxima
102 across the continental United States? Is there a dependence of these results on the
103 quantile of the GH distribution?

104

105 2. Data and Methodology

106 We analyze 1805 U.S. Geological Survey (USGS) stream gages with at least 14 water years
107 of daily GH data over the 1985-2015 period (Figure 1). These data are a subset of those used in
108 Slater and Villarini (2016), where all of the data processing details are provided. At each site, we
109 identify the largest daily GH value in every complete water year (defined as having at least 330
110 daily observations). In water years where two identical GH maxima were selected, we retain only
111 the earliest of the two.

112 To explain the year-to-year variations in GH annual maxima, we compute antecedent
113 wetness over the short term (“storm precipitation”) and long term (“basin wetness”) using
114 precipitation data from the PRISM Climate Group (e.g., Daly et al. 2002; available at
115 <http://prism.oregonstate.edu>). The spatial and temporal resolutions of this product are ~4km and
116 daily. Basin-averaged daily values are computed using the basin boundaries from USGS
117 Streamgage NHDPlus Version 1 Basins 2006. We use both shorter and longer precipitation
118 accumulations to reflect the relative role that storm precipitation and overall basin wetness play
119 for different quantiles of the GH distribution. As in Slater and Villarini (2016), storm

120 precipitation is computed for each annual GH maximum at every site by aggregating the basin-
121 averaged precipitation over the 10 days preceding and including the day of the peak; the basin
122 wetness is computed by aggregating the precipitation over the 365-day period that preceded the
123 storm precipitation. All 1805 sites had at least 14 annual GH maxima with antecedent storm
124 precipitation and basin wetness values.

125 We detect linear trends in the GH records using quantile regression (Koenker and Basset
126 1978, Koenker 2005). Briefly, quantile regression can be viewed as an expansion of the ordinary
127 least squares (OLS) approach. In OLS, the conditional mean of the response variable Y is
128 modeled with respect to one or more predictors, and the sum of the squared errors is minimized.
129 The idea behind quantile regression is to model the conditional quantile of Y in terms of
130 predictors. For instance, in median regression, where the quantile τ is equal to 0.5, the sum of the
131 absolute errors is minimized. By extending this approach to other τ quantiles, we minimize an
132 asymmetrically weighted sum of absolute errors to estimate the intercept and slope term(s). Here
133 we focus on τ quantiles ranging from 0.05 to 0.95 with a step of 0.05. The significance level for
134 the slopes is set at 5% (two-sided) and computed using bootstrap (no correction for potential
135 autocorrelation). In terms of predictors, we use time (year of event) to detect the presence of
136 temporal trends in the GH records, and total precipitation accumulated in a given window (10
137 days prior to maximum annual GH, and 365 days prior to the 10-day window), to improve our
138 understanding of what may have driven the inter-annual variability in different parts of the
139 extreme GH distribution.

140 An extensive discussion about the theoretical framework, application and references related
141 to quantile regression can be found in Koenker (2005). All the calculations were performed in R
142 (R Core Team 2016) using the freely available quantreg package (Koenker 2016).

143

144 3. Results

145 Analyses of temporal changes in the GH records using the Mann-Kendall test (Figure 2,
146 bottom-right panel) indicate that just 35 (77) sites have statistically significant increasing
147 (decreasing) trends, with the majority of the decreasing trends generally located in the southern
148 part of the United States. As previously discussed, however, the Mann-Kendall test focuses on
149 the central part of the conditional distribution of GH, potentially missing changes that occur at
150 the tails. Figure 2 shows that the broad separation of increasing/decreasing trends in the
151 northern/southern half of the continental United States is generally still detected using quantile
152 regression. However, as shown in Figure 2 and Supplementary Figure 1, more changes are
153 detected when we focus on low and high τ values, which suggests that the temporal changes in
154 GH are stronger at the lower and upper tails of the distribution. Furthermore, there are areas like
155 the U.S. Pacific Northwest where the lower quantiles of the GH distribution show increasing
156 trends, while the higher quantiles display the opposite tendency; this discrepancy points to a
157 narrowing of the GH distribution in the most recent years. Given the limited number of sites with
158 statistically significant results, we applied the Walker's test and the false discovery rate test
159 (Wilks 2006), and found that they were not field significant. The lack of a strong indication of

160 statistically significant trends may be due to the weak signal, the large noise associated with the
161 extremes, and to the limited (i.e., 30 years) record length.

162 Broadly speaking, these results are consistent with Slater and Villarini (2016), who found
163 that the frequency of exceedance of NWS flood levels was not uniform with the United States,
164 but rather characterized by a broad north/south divide. Slater and Villarini (2016), however,
165 found a greater proportion of sites with statistically significant trends in the number of annual
166 days above the NWS flood levels. By comparing all of these results, we find that the GH has not
167 been increasing in magnitude over the past 30 years, but rather that there have been changes in
168 the duration of flood level exceedance (increases or decreases depending on the location). One
169 possible research direction moving forward is to focus on the persistence of large-scale climate
170 conditions that are conducive to wetter/dryer periods, and to examine how these conditions may
171 have changed over the past 30 years.

172 In addition to the detection of temporal changes in GH extremes, we use quantile regression
173 to quantify the role played by storm precipitation and basin wetness for different parts of the GH
174 distribution (Figure 3). Storm precipitation is identified as a statistically significant predictor of
175 GH magnitude across large areas east of the 100th meridian and along the U.S. West Coast
176 (Figure 3, left panels). This is consistent with the expectation that liquid precipitation (i.e.,
177 rainfall) drives the occurrence of these flood events (e.g., Villarini 2016, Berghuijs et al. 2016).
178 In contrast, in the northern Great Plains, the Rocky Mountains, and the north-eastern United
179 States the flood events do not exhibit a statistically significant relationship with storm
180 precipitation, likely because the vast majority of these events are driven by snowmelt (e.g.,
181 Berghuijs et al. 2016). Overall, the central part of the GH distribution tends to be more closely
182 related to storm precipitation (Figure 4, top panel), possibly due to the use of a 10-day window
183 across all sites.

184 The results differ when we focus on the role played by basin wetness (Figure 3, right panels;
185 Figure 4, bottom panel). Most of the regions for which we did not find a statistically significant
186 relationship with storm precipitation (e.g., northern Great Plains and Rocky Mountains) do
187 present a statistically significant relationship with basin wetness. The dependence of these results
188 on conditional quantiles is also different from the results that were found using storm
189 precipitation as a predictor. As shown in Figure 4 (bottom panel), the number of significant sites
190 decreases for increasing τ values; basin wetness is a significant predictor for 489 sites at $\tau=0.05$,
191 but only for 298 sites at $\tau=0.95$. These results are consistent with Wood et al. (1990) and Smith
192 et al. (2013), who found that the role played by antecedent soil moisture conditions diminishes as
193 flood events become more extreme.

194

195 4. Summary and Conclusion

196 We analyzed daily GH records at 1805 USGS sites across the continental United States using
197 quantile regression. Our focus was on the detection of trends in the annual maximum GH series,
198 and the relationship between these maxima and precipitation accumulated in the 10 days (i.e.,

199 storm precipitation) and 365 days (i.e., basin wetness) prior to their occurrence. Our findings can
200 be summarized as follows:

- 201 - The temporal changes in the United States exhibit regional differences, with the northern
202 (southern) half pointing to increasing (decreasing) trends. These trends vary across
203 different parts of the GH distribution, and are generally more frequently detected towards
204 the tails of the distribution.
- 205 - Results based on the Mann-Kendall test, which focuses on the central part of the
206 distribution, suggested a more muted signal of change. The use of quantile regression, in
207 contrast, provides a more comprehensive perspective on the changes occurring in
208 different parts of the distribution.
- 209 - The results from the trend detection analyses are not field significant, suggesting that
210 when a signal of change is present, the signal may be weak or the level of noise in the
211 data may be large, likely due to the shortness of record length.
- 212 - Storm precipitation is an important explanatory variable for the areas of the country
213 where flood events are tied to rainfall (e.g., east of the 100th meridian, U.S. West Coast).
214 The role of basin wetness becomes more relevant in areas where snowmelt represents a
215 more dominant flood generating mechanism (e.g., northern Great Plains, Rocky
216 Mountains).
- 217 - The role of basin wetness decreases as events become more extreme, consistent with a
218 diminished role played by antecedent soil moisture conditions for more extreme flooding.

219 The examination of changes in annual maximum precipitation and annual precipitation
220 (Supplementary Figure 2) indicates that the broad north-south divide found in GH is equally
221 reflected in the precipitation records, with local differences likely driven by changes in land
222 surface / land cover and water management. Future studies could take our attribution results
223 further by examining the role of human-induced climate change on precipitation and
224 consequently on flooding across the United States (e.g., van der Wiel et al., 2016; Wang et al.,
225 2016).

226
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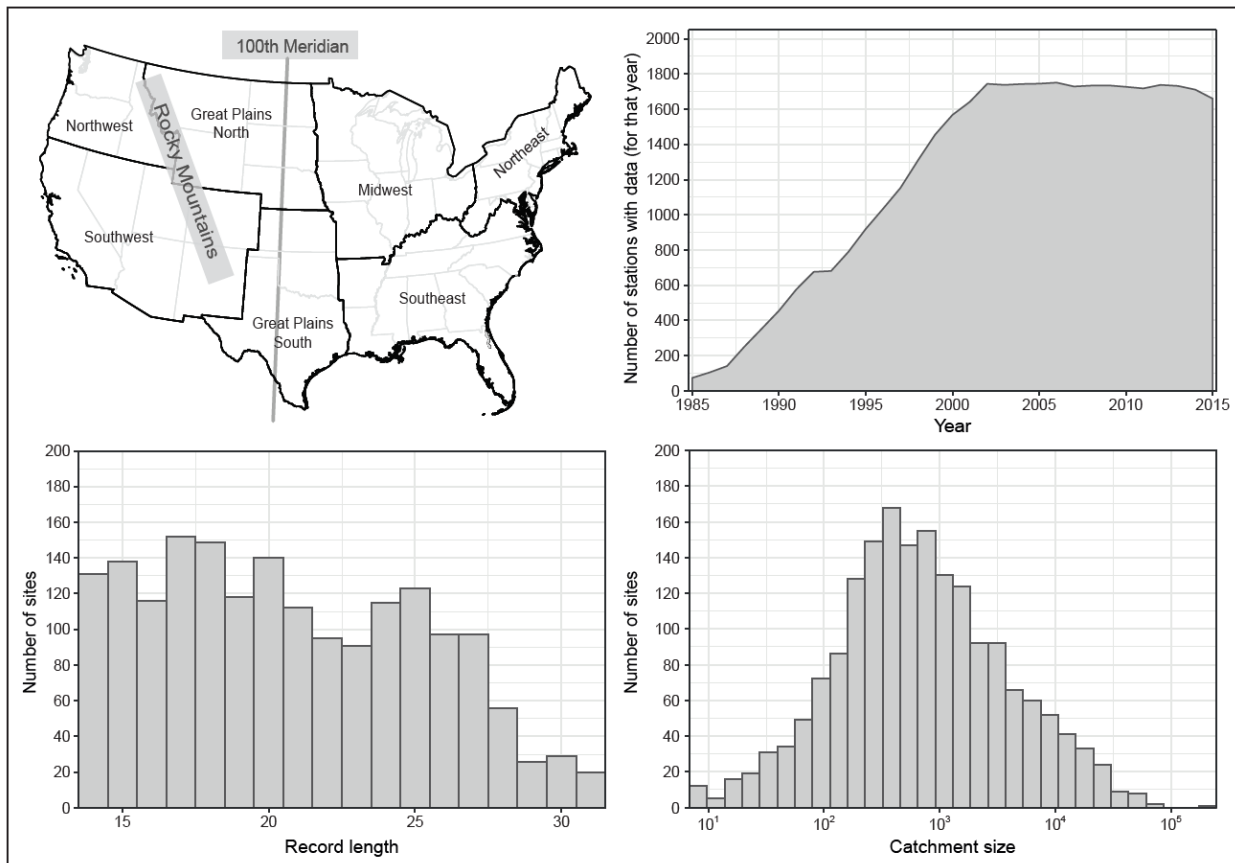
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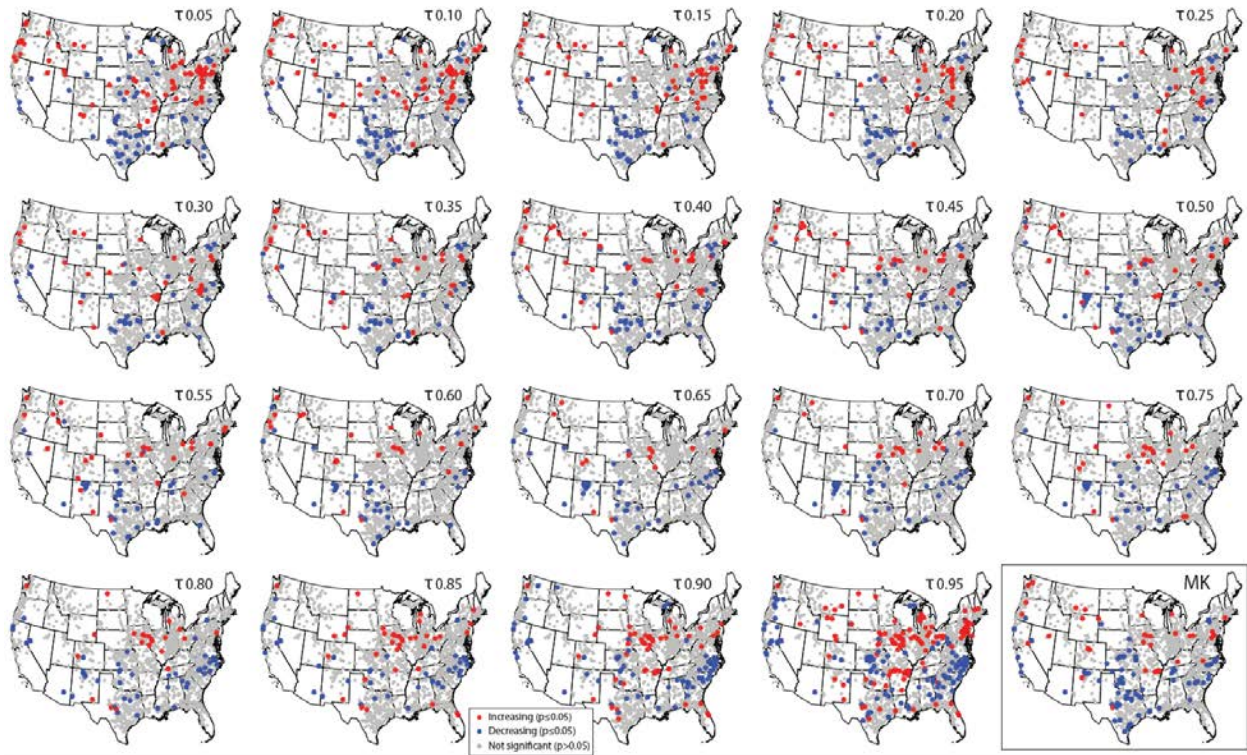
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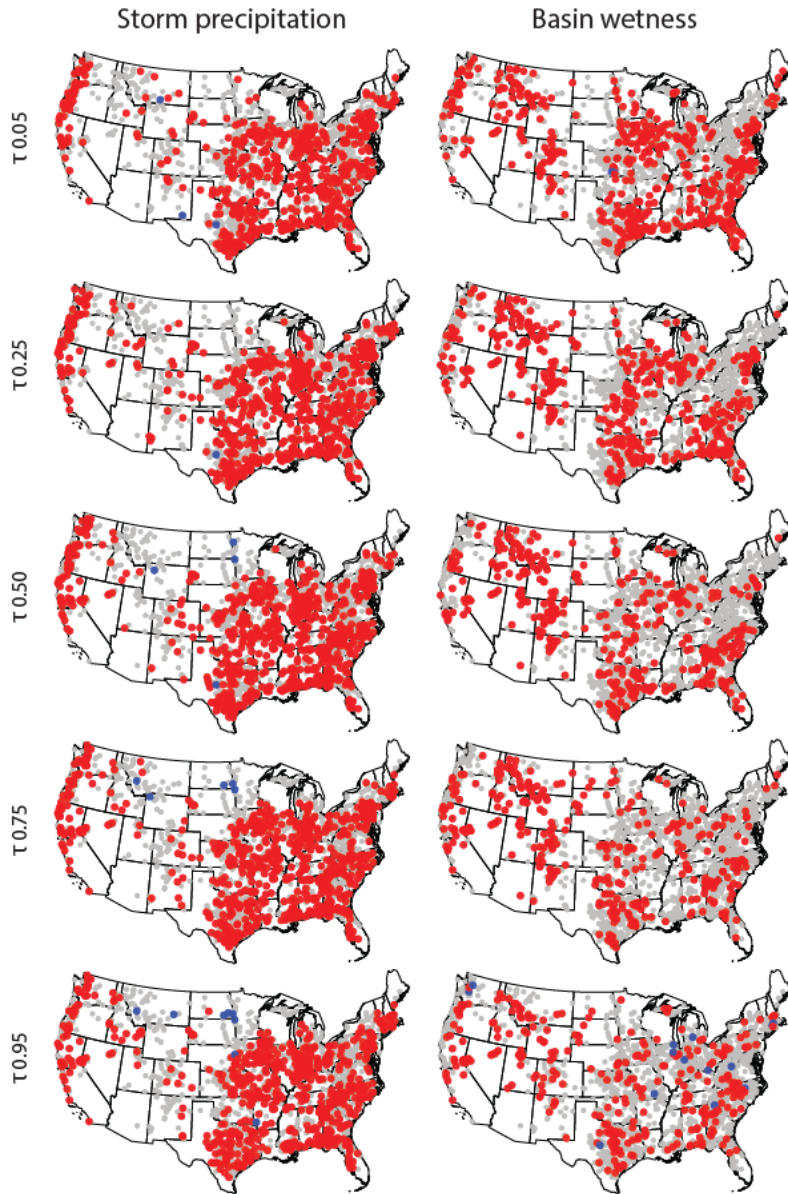
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292 Figure 1: Descriptive statistics for the 1805 USGS sites considered in this study. Map indicating
 293 seven broad regions in the continental United States; Histograms showing the number of stations
 294 with data in every year, record length, and catchment size.



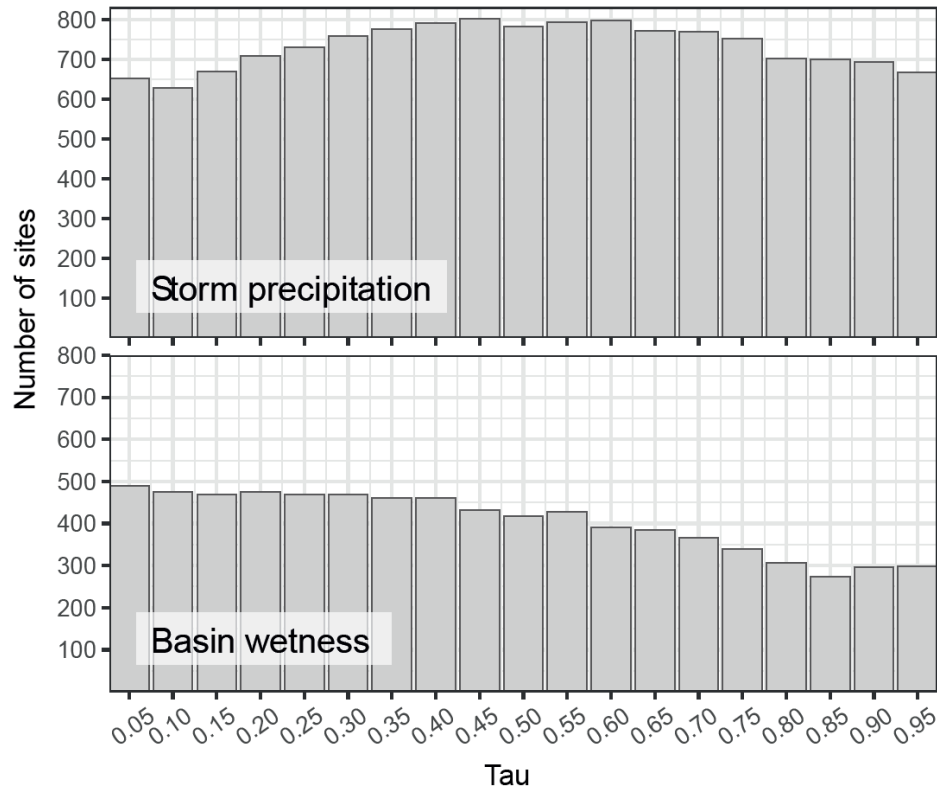
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296 Figure 2: Temporal trends in flood stage at the 1805 USGS sites. The results are based on
 297 quantile regression (τ from 0.05 to 0.95 with a step of 0.05) and the Mann-Kendall test (bottom-
 298 right panel). The results are significant at the 5% level.



299

300 Figure 3: Maps showing the USGS stations for which storm precipitation (left panels) and basin
 301 wetness (right panels) are statistically significant predictors (at the 5% level). Rows indicate
 302 different values of τ (0.05, 0.25, 0.50, 0.75, 0.95).



303

304 Figure 4: Histogram showing the number of sites for which storm precipitation (top panel) and
 305 basin wetness (bottom panel) are positively and statistically significantly (at the 5% level) related
 306 to the gage height records for different τ values.