Nonstationary Extreme Precipitation Frequency Analysis in the Gulf Coast

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April 16, 2023

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MOTIVATION

- Engineering design, risk assessment, and floodplain management rely on estimates of heavy rainfall probabilities
- Anthropogenic climate change affects the frequency, magnitude, and characteristics of heavy rainfall
- Current guidance (e.g., Atlas 14) assumes stationarity

Figure 1 Addicks Reservoir in Houston in August 2017 during Harvey (David J. Phillip/Associated Press)

RESEARCH GAP

Estimating nonstationary rainfall probabilities from limited observation data leads to large parametric uncertainty. For example, applying the same analysis to nearby gauges can yield very different estimates of return periods and trends (figure 2).

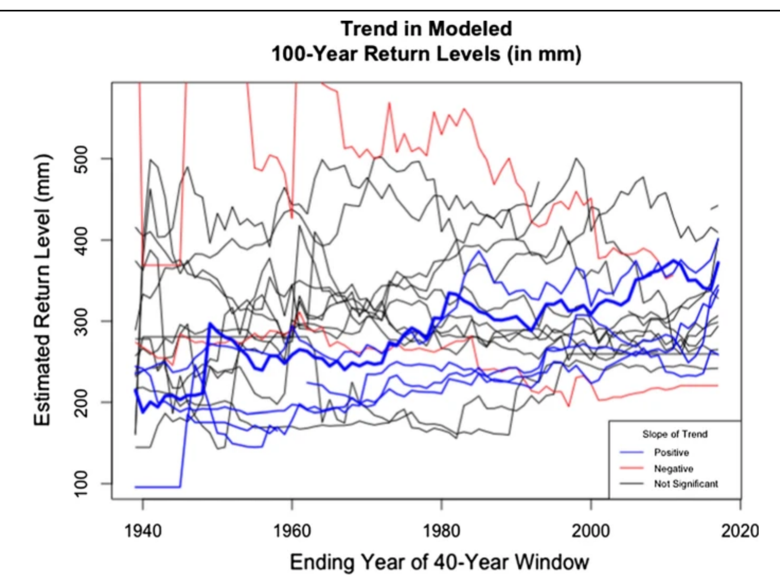

Figure 2 moving window 100 year return level modeled for stations in Southeast Texas (Fagnant et al., 2020)

RESEARCH QUESTION

What robust changes in heavy rainfall probabilities are evident in the historical record?

METHODOLOGY

Key assumption: the effects of climate indices on heavy rainfall probabilities are spatially coherent.

- Annual maximum rainfall extracted from Global Historical Climatology Network (GHCN) daily dataset
- CO_2 concentrations data from Law Dome and Mauna Loa
- Annual maximum rainfall at location *s* and year *t* follows the Generalized Extreme Value (GEV) distribution

$$y(s,t) \sim GEV(\mu(s,t), \sigma(s,t), \xi(s))$$

- GEV parameters are conditioned on climate time series $x_j(t)$ (log of global CO_2 concentration and Niño 3.4)

$$\mu(s,t) = \mu_0(s) + \sum_{j=1}^{J} \beta_j^{\mu}(s) x_j(t) \qquad \sigma(s,t) = \sigma_0(s) + \sum_{j=1}^{J} \beta_j^{\sigma}(s) x_j(t)$$

- Semi-Bayesian framework (Ossandón et al, 2021): fit Gaussian Process to interpolate point estimates

Climate Change Contributes to Increase in Extreme Precipitation Variability

- There are spatially coherent patterns for all coefficients, but with large variability between nearby stations, suggesting a strong role for random variability
- Log CO_2 has a stronger impact on the scale parameter than the location parameter, suggesting that climate change is driving an increase in extreme precipitation variability

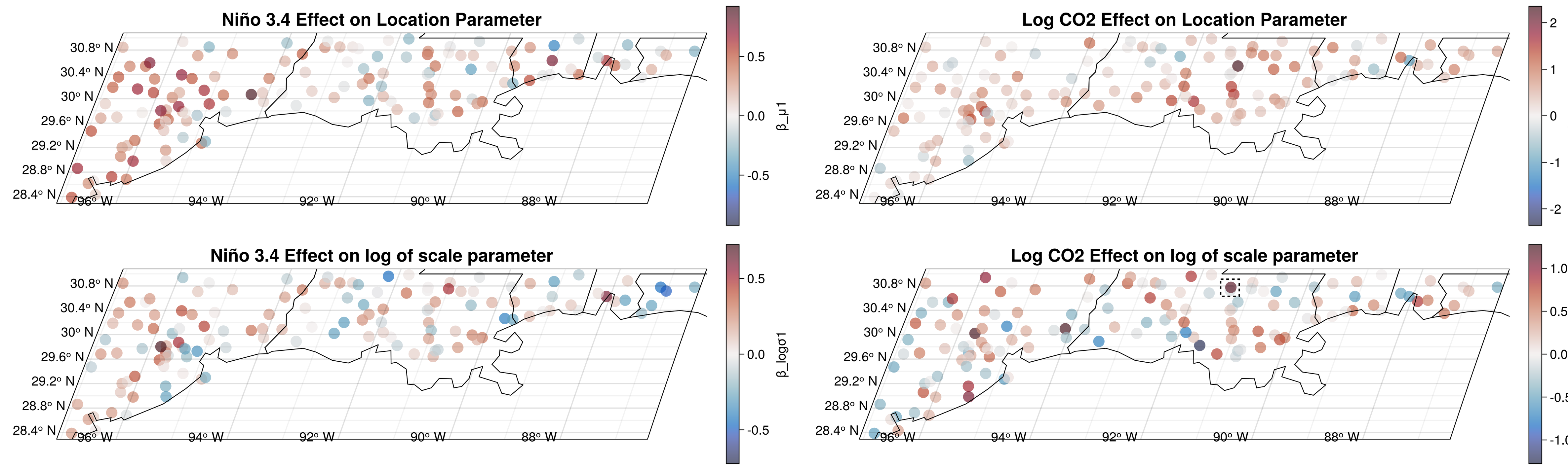

Figure 1 The coefficients of (L) Niño 3.4 SST anomalies Index and (R) the anomalies of log of CO2 concentration on (T) the location and (B) the scale parameters of the model. Units of location and scale parameters are inches, CO2 is in ppm, and the Niño 3.4 index is in °C

Increases in Heavy Rainfall Probabilities

- Log CO_2 contributes to increase in 10 and 100 year return levels for most stations
- Different signs for changes are estimated for some nearby locations
- Spatial patterns are similar for the 10 and 100 year return levels, with highest return levels near Houston (TX) and Mobile (AL)
- Results consistent with prior work (e.g., Atlas 14; Nielsen-Gammon, 2020)

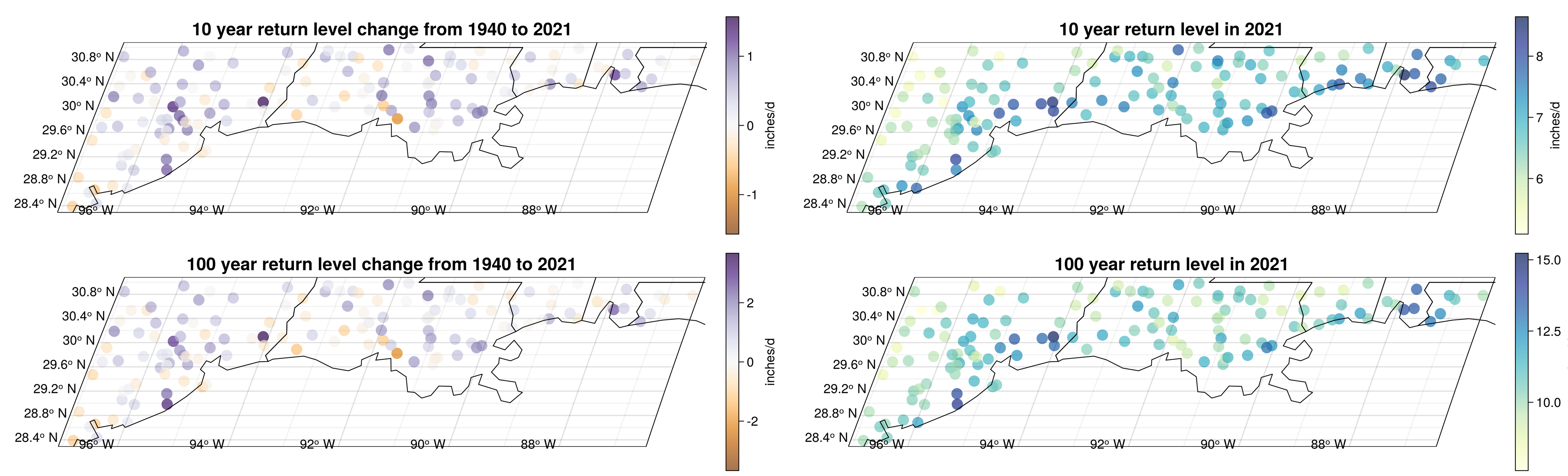

Figure 3 Return levels estimations based on non stationary point analysis LogCO_2 without spatial pooling

KEY FINDINGS

- **Heavy rainfall probabilities increase at most stations, but estimates are not robust**
- **Climate change signal is consistent with increasing interannual variability of heavy rainfall**
- **Gaussian Process smoothing produces credible inferences (see Future Work)**

NEXT STEPS

- Full Bayesian inference, i.e. Monte Carlo sampling from the full posterior distribution
- Different durations and seasons
- Incorporate paleoclimate reconstructions

Need for More Robust Estimations

- The latter station has a clear positive trend while the former one has highly uncertain trend
- Missing values and the high observations in 2016 and 2017 contribute to the difference in return level estimations

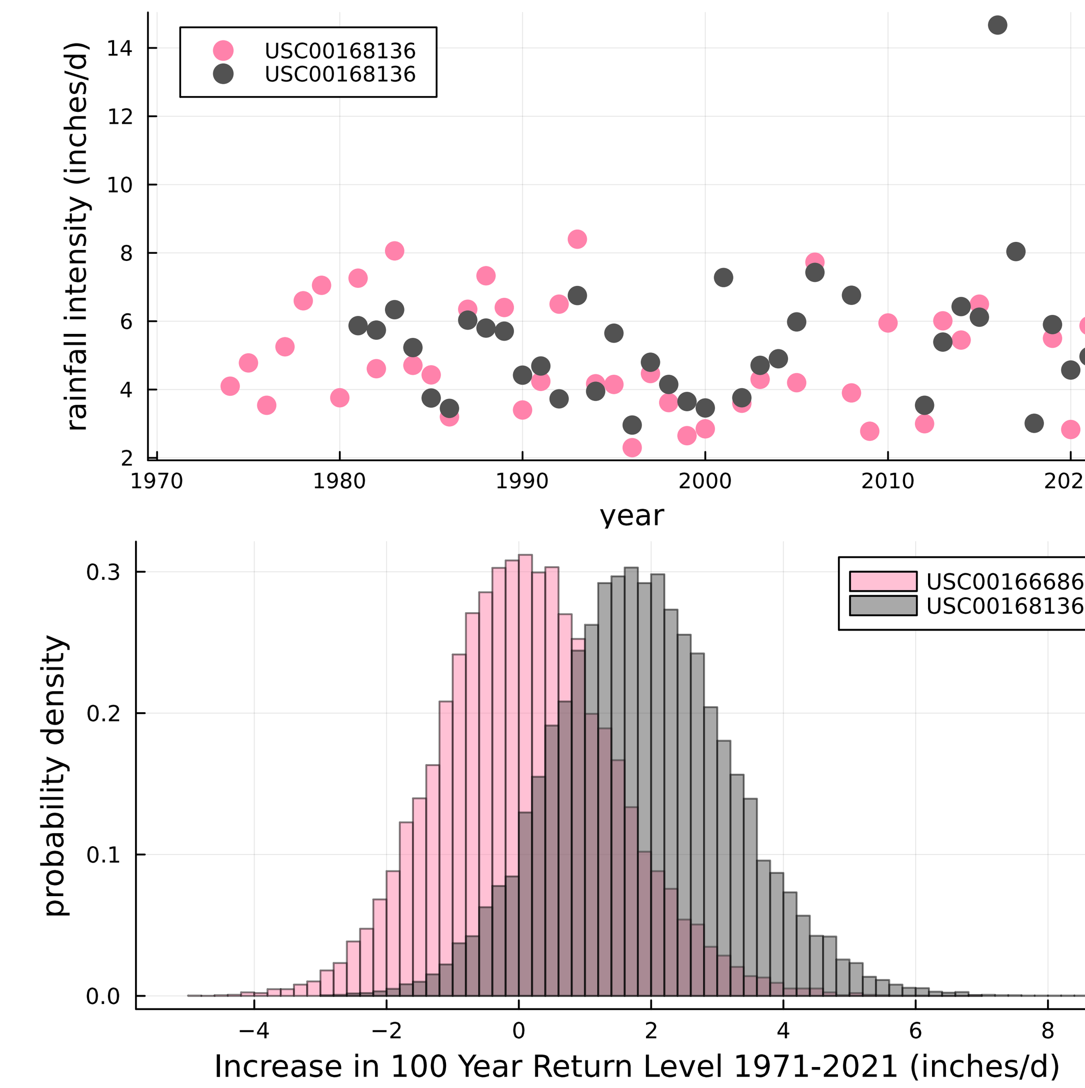

Figure 2 (T) Annual maximum precipitation from 1971 to 2021 for two nearby locations (boxed in RB Figure 1) (B) Difference between 100 year return level in 1971 and 2021(inches/d) estimated with the full Bayesian approach at each station

Spatial-Temporal Model

- GEV parameters are interpolated using a Gaussian Process to estimate precipitation return levels at new locations
- This method results in smoother return level estimations, emphasizes the pattern of higher precipitation along the coast

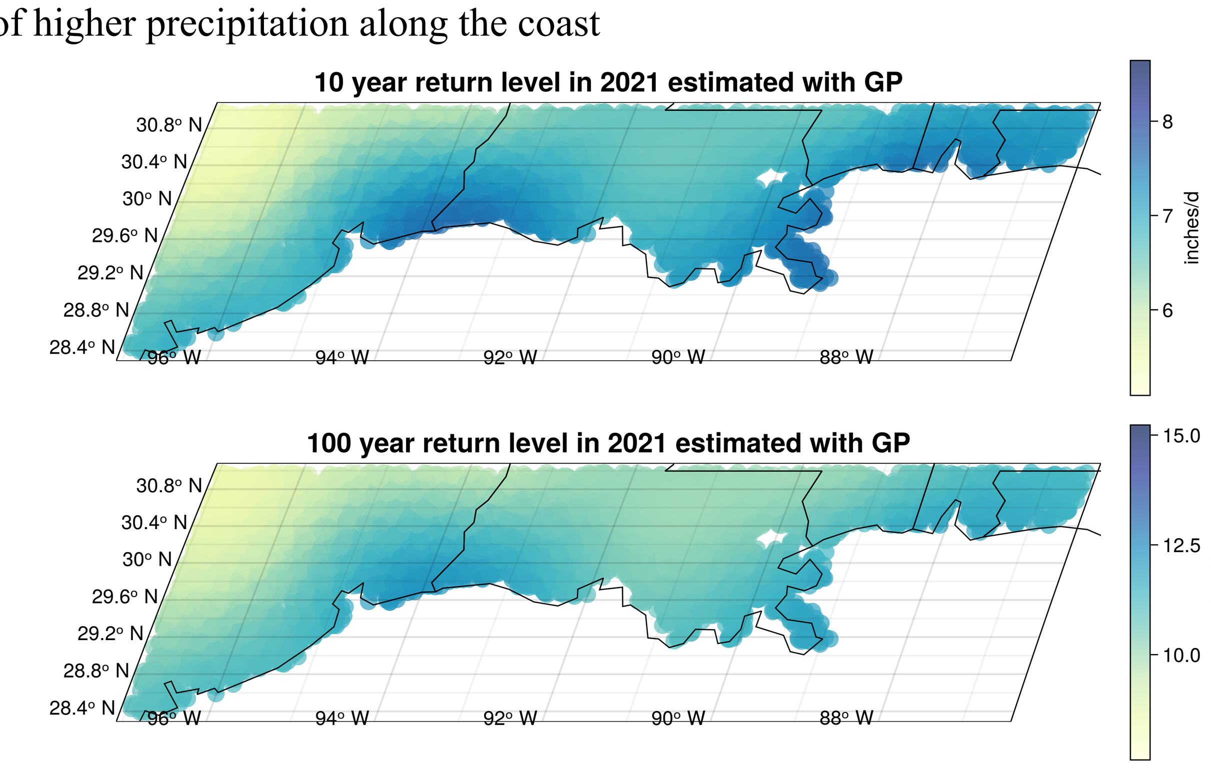

Figure 4 Spatially pooled 10/100 year events

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