

Yuchen Lu¹, Benjamin Seiyon Lee², and James Doss-Gollin¹

¹Department of Civil and Environmental Engineering, Rice University

²Department of Statistics, George Mason University

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Abstract

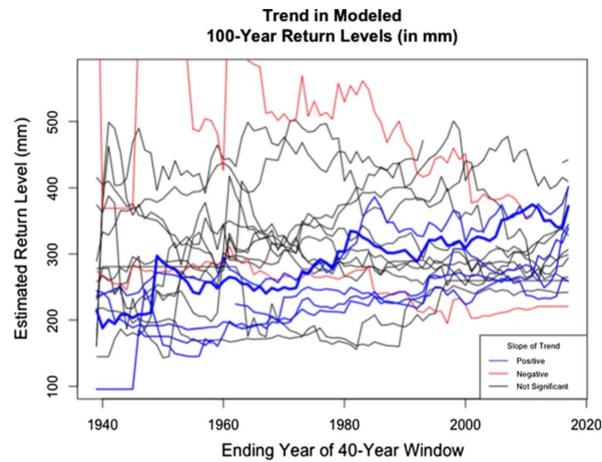
Precipitation exceedance probabilities play a critical role in engineering design, risk assessment, and floodplain management. While climate variability and change impact the frequency and intensity of heavy rainfall, the assumption that extreme precipitation is stationary in time, as implemented in official guidance like Atlas 14, can underestimate present and future hazards. Previous studies show that conditioning the statistical distribution parameters on time-varying climate covariates can improve estimates of nonstationary precipitation frequencies. However, this approach increases the number of parameters to be estimated, exacerbating parametric uncertainty. To address this, we propose a nonstationary and spatially varying model for process-informed precipitation frequency analyses. Specifically, we assume that the robust effects of climate covariates on the probability distribution of extreme rainfall are heterogeneous in space. We employ a hierarchical Bayesian model, leveraging Gaussian processes and extreme value theory, and apply this model to infer nonstationary rainfall exceedance probabilities for the Western Gulf Coast. The proposed approach is highly flexible, naturally allows the use of stations with incomplete observational records, identifies robust temporal trends along with smooth return level estimates, and quantifies parametric uncertainty. This framework can be used to improve adaptation guidance (such as IDF curves) in other regions.

Motivation

Estimates of precipitation frequency are widely used in risk assessment and management. Yet despite recognition that interannual variability and **climate change** affect hazards, most current guidance (e.g. Atlas 14) assumes **stationarity**.

Knowledge Gap

Incorporating nonstationarity into precipitation frequency estimates can dramatically amplify **parametric uncertainty**. Here, we demonstrate how hierarchical **spatial pooling** can enhance inference for nonstationary extreme value models.



Fagnant et. al (2020): moving window analysis on stations in SE Texas and W Louisiana. Estimated precipitation frequencies and trends vary dramatically between nearby stations, motivating more robust estimation strategies.

Methodology

We assume that the impacts of climate on extreme precipitation characteristics are spatially coherent, represented by a **latent spatial field** describing the smoothly varying GEV parameters (details provided below).

Bayesian Hierarchical Model

Annual maximum rainfall at location s and year t follows the Generalized Extreme Value (GEV) distribution

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

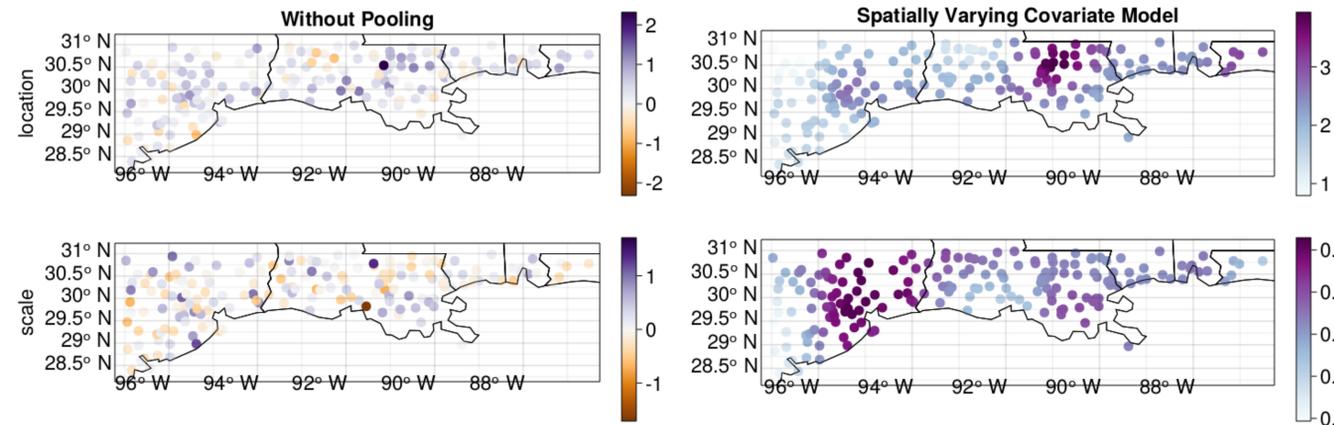
Process-Informed Nonstationary Model

We condition the GEV parameters on climate time series $x_j(t)$ (log of global CO₂ concentration)

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

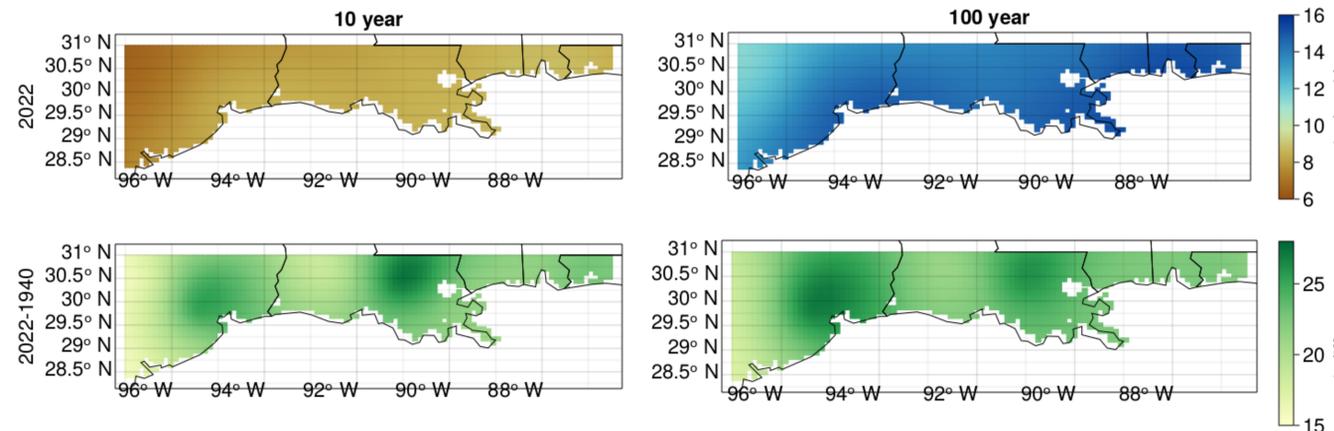
Latent parameters are smooth in space, implemented with a **Gaussian Process hierarchical prior**. We conduct **Bayesian Inference** via Markov Chain Monte Carlo.

Robust Trends in Extreme Precipitation



Posterior mean of coefficients of the anomalies of log of CO₂ concentration on (T) the location and (B) the scale parameters estimated from (L) nonstationary model at separate stations and (R) spatially varying covariate model

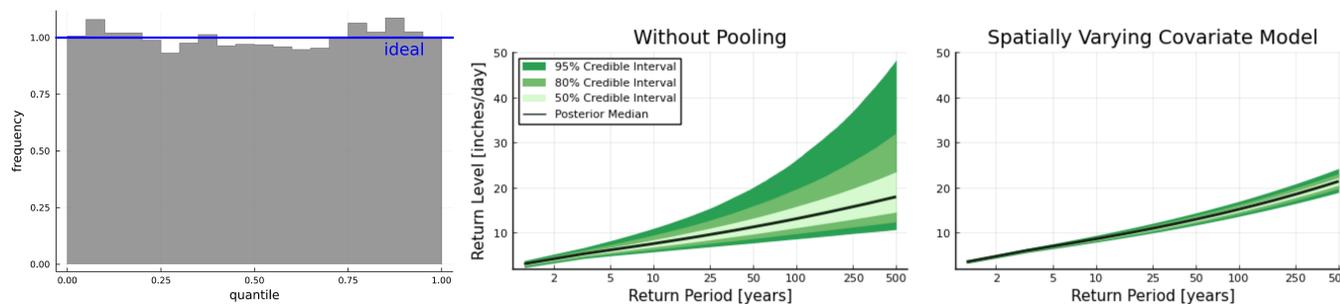
Spatially Consistent Increases in Heavy Rainfall Probabilities



Posterior mean of return levels estimates (T) in 2022 (B) difference between 2022 and 1940 for the (L) 10 year and (R) 100 year return periods

Well Calibrated and Reduced Uncertainties

Our Spatially Varying Covariate Model improves estimates by (1) reducing uncertainty compared to conventional nonstationary model simulated at separate stations and (2) achieving statistical calibration.

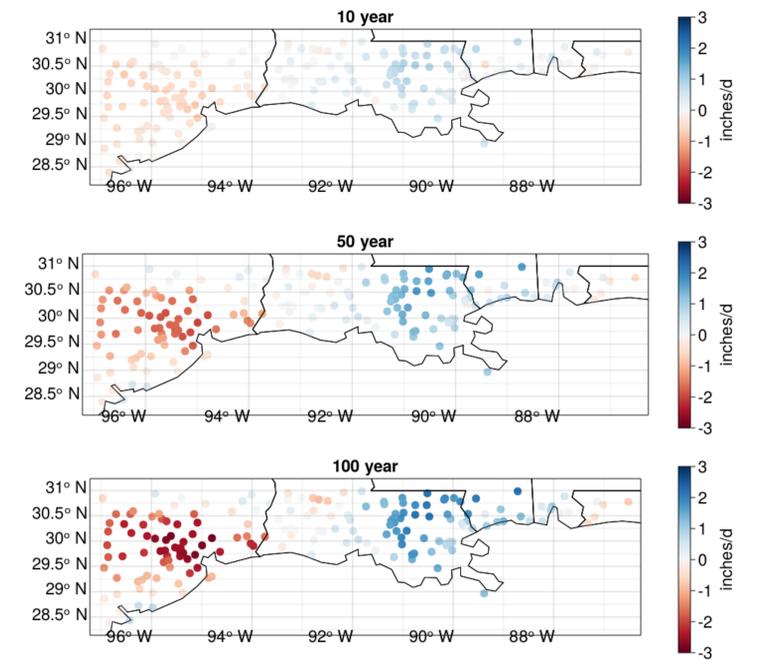


(L) Quantiles of the observation records given the simulated posterior GEV distributions. An ideal model would have a uniform distribution. Return level estimates in Houston with uncertainty boundary using (M) nonstationary model at separate stations (R) Spatially Varying Covariate Model

Comparison with Atlas 14

	Atlas 14	Spatially Varying Covariate Model
Stationarity	Stationary	Process-Informed Nonstationarity
Regionalization	Region of Influence	Hierarchical Gaussian Process
Inference	L-moments	Bayesian Inference

We estimate **higher current (2022) hazard** than Atlas 14 in most of the domain. Our current estimates are lower in the area directly impacted by Hurricane Harvey (SE Texas; 2017).



Return level estimates from the spatially varying covariate model minus that from Atlas 14

Conclusions

Our **Spatially Varying Covariates** model:

1. Identifies robust and spatially coherent trends
2. Improves estimation

We find **increasing risk of 24-hour precipitation** over the study area driven by climate change. This model can be used for IDF curves and to other spatially and temporally varying climate hazards.

References

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