Spatial Bayesian Hierarchical Model for Summer Extreme Precipitation over the Southwest U.S.

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Abstract

The Southwest U.S. comprising of the four states-Arizona, New Mexico, Colorado, and Utah-is the hottest and driest region of the United States. Most of the precipitation arrives during the winter season, but the summer precipitation makes a significant contribution to the reliability of water resources and the health of ecology. However, summer precipitation and its extremes, over this region exhibit high degree of spatial and temporal variability. In this study we developed a novel spatial Bayesian hierarchical model to capture the space-time variability of –summer season 3-day maximum precipitation over the southwest U.S. In modeling framework, the data layer the extremes at each station are assumed to be distributed as Generalized Extreme Value (GEV) distribution with non-stationary parameters. In addition, the extremes across space is assumed to be related via a Gaussian Copula. In the process layer, the parameters are modeled as a linear function of large scale climate variables and regional mean precipitation covariates. This is akin to a Generalized Linear Model (GLM). The parameters of the covariates at each station are spatially modeled using spatial Gaussian processes to capture the spatial dependency and enable generating the spatial field of the hydroclimate extremes. The likelihood estimates of the GLM at each station form the initial priors. The posterior distribution of the model parameters and consequently the predictive posterior GEV distribution of the hydroclimate extremes at any arbitrary location, or grid and for any year are obtained. The model is demonstrated by application to extreme summer precipitation at 73 stations from this region. The model validation indicates that return levels and their associated uncertainty have a well-defined spatial structure and furthermore, they capture the historical variability very well. The posterior distribution of the GEV parameters were generated on a 1/8th degree grid, providing maps of various return levels for all the years. Maps of return levels provide information about the spatial and temporal variations of the risk of extreme precipitation in the Southwest U.S. that will be of immense help in management and planning of natural resources and infrastructure.

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INTRODUCTION

The Southwest U.S. comprising of the four states -Arizona, New Mexico, Colorado, and Utah- is the hottest and driest region of the United States.

Most of the precipitation arrives during the winter season, but the summer precipitation makes a significant contribution to the reliability of water resources and the health of ecology.

Summer precipitation and its extremes, over this region exhibit high degree of spatial and temporal variability.

We developed a novel spatial Bayesian hierarchical model to capture the space-time variability of summer season 3-day maximum precipitation over the southwest U.S.

STUDY AREA AND DATA

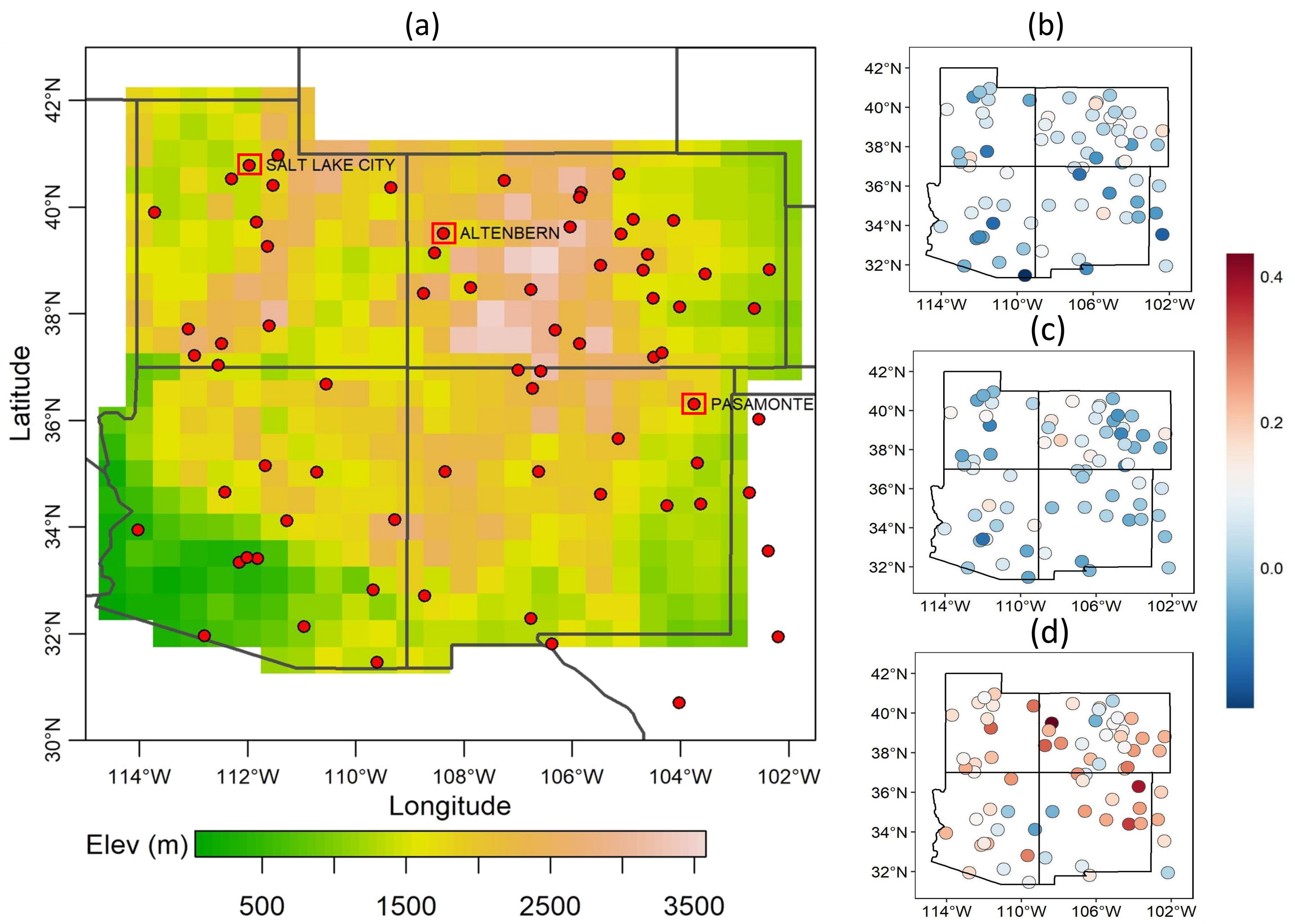

***Figure 1**. (a) 0.5° elevation grid in (m), station location as red points, and red boxes correspond to stations selected for uncertainty analysis. Correlation between summer 3-day maximum precipitation and covariates: (b) ENSO; (c) PDO; (d) Spatial average of seasonal total precipitation.*

Precipitation

- Daily observed precipitation - Global Historical Climatology Network (GHCN) dataset (https://www1.ncdc.noaa.gov/pub/data/ghcn/daily/)
- Years: 1964-2018, no. of stations 73.
- Seasonal total and 3-day maximum precipitation were computed from daily precipitation.

Covariates

- Elevation data - NASA Land Data Assimilation Systems (NLDAS) (https://ldas.gsfc.nasa.gov/nldas/elevation)
- ENSO and PDO climate indices (https://www.esrl.noaa.gov/psd/data/climateindices/list/)
- Spatial average of seasonal total precipitation.

MODEL STRUCTURE

Data Layer

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

Where

$$\mu(s,t) = \alpha_1(s) + \alpha_2(s)ENSO(t) + \alpha_3(s)PDO(t) + \alpha_4(s)\bar{P}_T(t)$$
$$\sigma(s) = \exp(\alpha_5(s))$$
$$\xi(s) = \alpha_6(s)$$

Process Layer

$$\begin{bmatrix} \boldsymbol{\alpha}_{1(m\times1)} \\ \boldsymbol{\alpha}_{2(m\times1)} \\ \boldsymbol{\alpha}_{3(m\times1)} \\ \boldsymbol{\alpha}_{4(m\times1)} \\ \boldsymbol{\alpha}_{5(m\times1)} \\ \boldsymbol{\alpha}_{6(m\times1)} \end{bmatrix} = \boldsymbol{X}_{(m\times4)} \begin{bmatrix} \boldsymbol{\beta}_{\alpha_1(1\times4)} \\ \boldsymbol{\beta}_{\alpha_2(1\times4)} \\ \boldsymbol{\beta}_{\alpha_3(1\times4)} \\ \boldsymbol{\beta}_{\alpha_4(1\times4)} \\ \boldsymbol{\beta}_{\alpha_5(1\times4)} \\ \boldsymbol{\beta}_{\alpha_6(1\times4)} \end{bmatrix}^T + \mathbf{w}_{s(6m\times1)} + \mathbf{w}_{ns(6m\times1)}$$

Where

$X(s) = \{1, Long(s), Lat(s), Elev(s)\}$

$\mathbf{w}_{s(6m\times1)}$: Spatial random effect that follow a 0 mean multivariate Gaussian process

$$\mathbf{w}_{s(6m\times1)} \sim MVN(\mathbf{0}_{(6m\times1)}, \boldsymbol{\Sigma}_{s(6m\times6m)})$$

$$\boldsymbol{\Sigma}_{s(6m\times6m)} = \begin{bmatrix} C_{11}(\theta) & \cdots & C_{16}(\theta) \\ \vdots & \ddots & \vdots \\ C_{61}(\theta) & \cdots & C_{66}(\theta) \end{bmatrix}$$

$$C_{kk}(\theta) = \delta_k^2 \exp(-a_k||s_i - s_j||)$$
$$C_{kp}(\theta) = \delta_{kp}^2 \exp(-a_{kp}||s_i - s_j||)$$

$\mathbf{w}_{ns(6m\times1)}$: Non spatial random effect that follow a 0 mean multivariate Gaussian process

$$\mathbf{w}_{s(6m\times1)} \sim MVN(\mathbf{0}_{(6m\times1)}, \boldsymbol{\Sigma}_{ns(6m\times6m)})$$

$$\boldsymbol{\Sigma}_{ns(6m\times6m)} = \begin{bmatrix} \tau_1^2 & 0 & \cdots & 0 \\ 0 & \tau_2^2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \tau_6^2 \end{bmatrix}$$

RESULTS

Bayesian Multivariate Simulations

5000 simulations from posterior distributions of the model parameters were obtained on a 0.5° grid (Figure 1a).

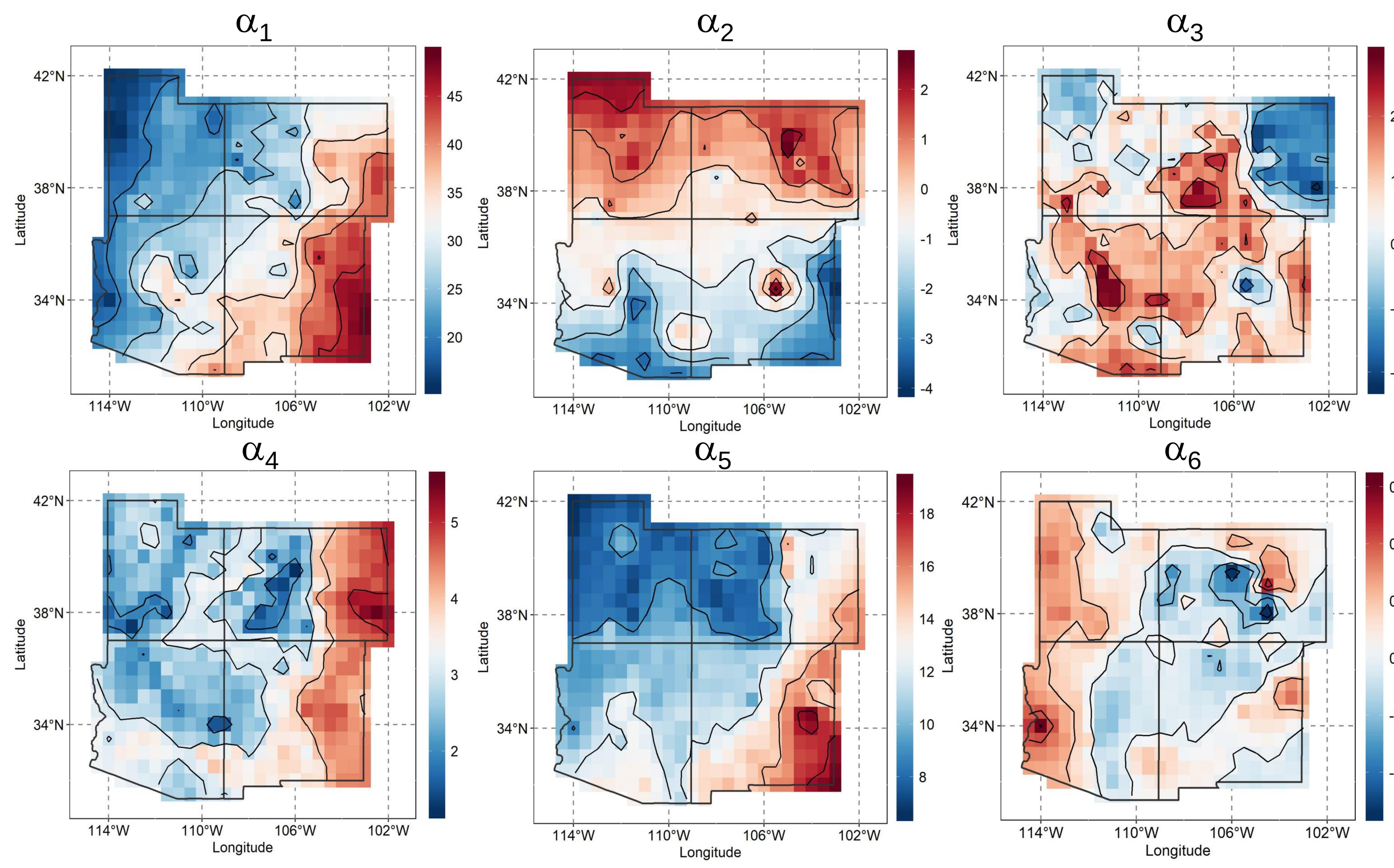

***Figure 2**. Posterior Median of the GEV parameters*

Nonstationary return levels over a grid

Spatial and Temporal return levels for 2 and 100-year for seasonal 3-day maximum precipitation from the posterior GEV distributions are shown below.

Spatial Variability of Return Levels

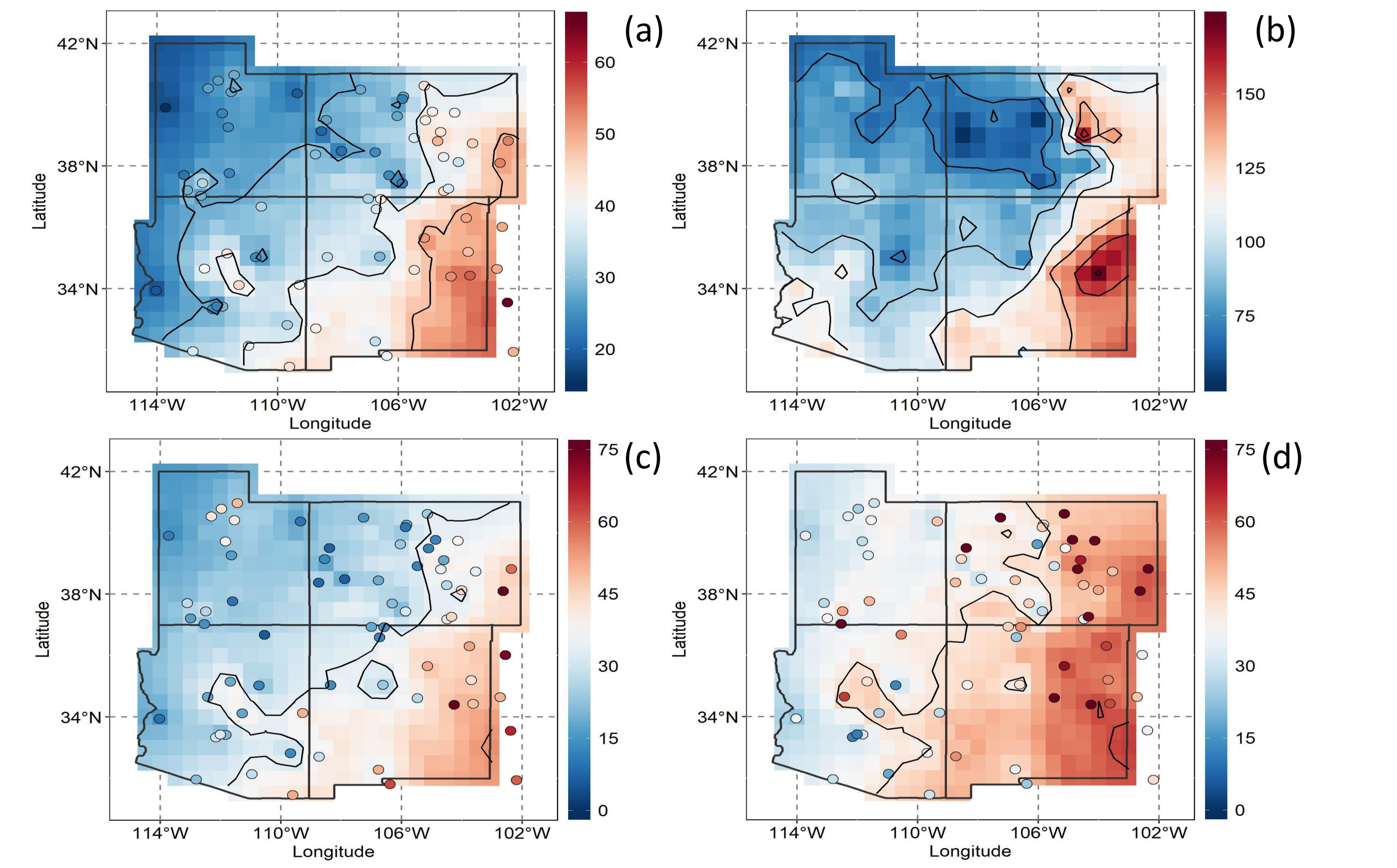

***Figure 5**. (a) Median of T=2 years 3-day maximum precipitation along with the median of the observed. (b) Median of T=100 years 3-day maximum precipitation, (c) Median of T=2 years 3-day maximum precipitation for a dry year (1978) along with the of the observed, (d) Median of T=2 years 3-day maximum precipitation for a wet year (1997) along with the of the observed.*

- Spatial map of 2-year return level (i.e. median) matches very well with the observed data
- 100-year return level shows a similar spatial pattern to that of the 2-year return level, i.e., higher precipitation in the east and lower in the west
- For the wet and dry years the patterns are similar with consistent magnitudes, except for small pocket in northern UT during dry years

Temporal Variability of Return Levels

posterior GEV distribution for each year are shown below.

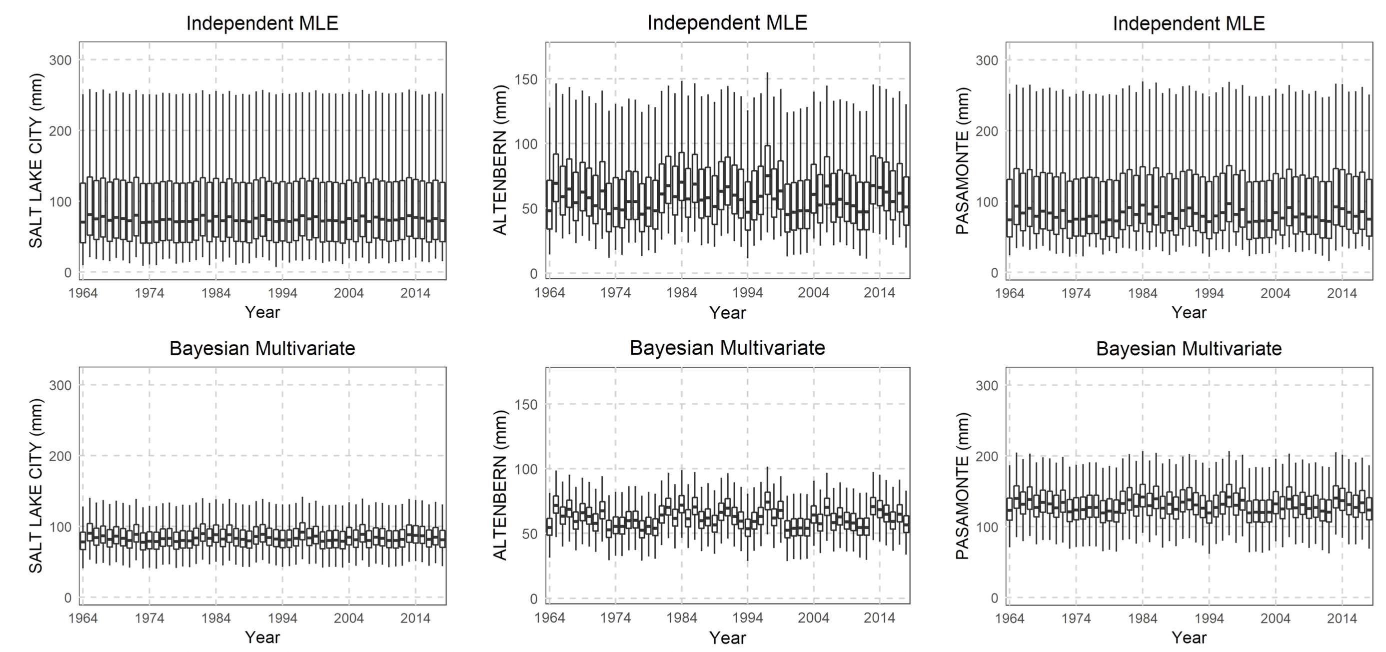

***Figure 4**. Independent MLE (top row) and Bayesian multivariate nonstationary (bottom row) 100-year return levels for Salt Lake City, UT (left column), Alterbern, CO (middle column), and Pasamonte, NM (right column).*

- Two models shows similar inter-annual variability
- Bayesian multivariate model shows significant reduction in the uncertainty

CONCLUSIONS

- Bayesian space-time hierarchical model
  - captures the spatial and temporal patterns quite well and provides robust estimation of uncertainties
  - Reduced uncertainty estimates compared to MLE
- Additional Skillful covariates can further improve the estimates of space-time variability

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