Variability of Hydroclimate Extremes on Seasonal to Multidecadal Time Scales in the Western US

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RECLAMATION

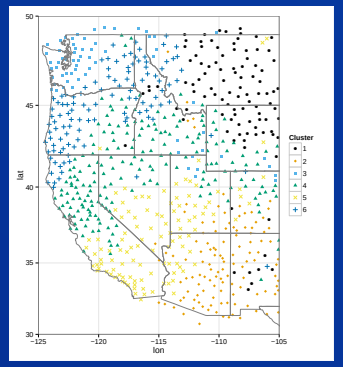
Flood Frequency Variability on Seasonal to Multidecadal Time Scales in the Western US and Implications for Infrastructure Planning

Gaps Addressed

- LT 4.03 - method and basis for estimating extreme hydrologic event possibilities in a changing climate

Research Questions

1. How are winter extreme flooding events manifested in the western US? Specifically, what atmospheric and hydrologic ingredients conspire to produce extreme flood events at seasonal and multidecadal time scales?
2. How can this understanding be employed to model flood frequency in space and time, and under a changing climate?
3. What are the implications for long-term infrastructure planning (e.g., dam safety, levee protection, etc.) and management?



Identification of spatial coherence in extreme precipitation events

Collaborators/Schedule/Source of Support

- Reclamation, University of Colorado
- Project started in FY13, continued support FY14
- S&T 1916

RECLAMATION

Goals/Outline

How are winter extreme flooding events manifested in the western US?

- Parallel analysis of streamflow and precipitation extremes in the western US
- Data Sources (Flow and Precip)
- Data Diagnostics
  - Clustering

What atmospheric and hydrologic ingredients conspire to produce extreme flood events at seasonal and multidecadal time scales?

- Climate covariates

How can this understanding be employed to model flood frequency in space and time, and under a changing climate?

- Extreme Value Analysis (Stationary and Nonstationary)
  - Model flood frequency in space and under changing change

Data

Flow
The Hydro-Climatic Data Network (HCDN) 2009 is an updated list of relatively unimpaired sites that have been identified as suitable for hydro-climatic study by the USGS (Falcone et al. 2010; Falcone 2011).

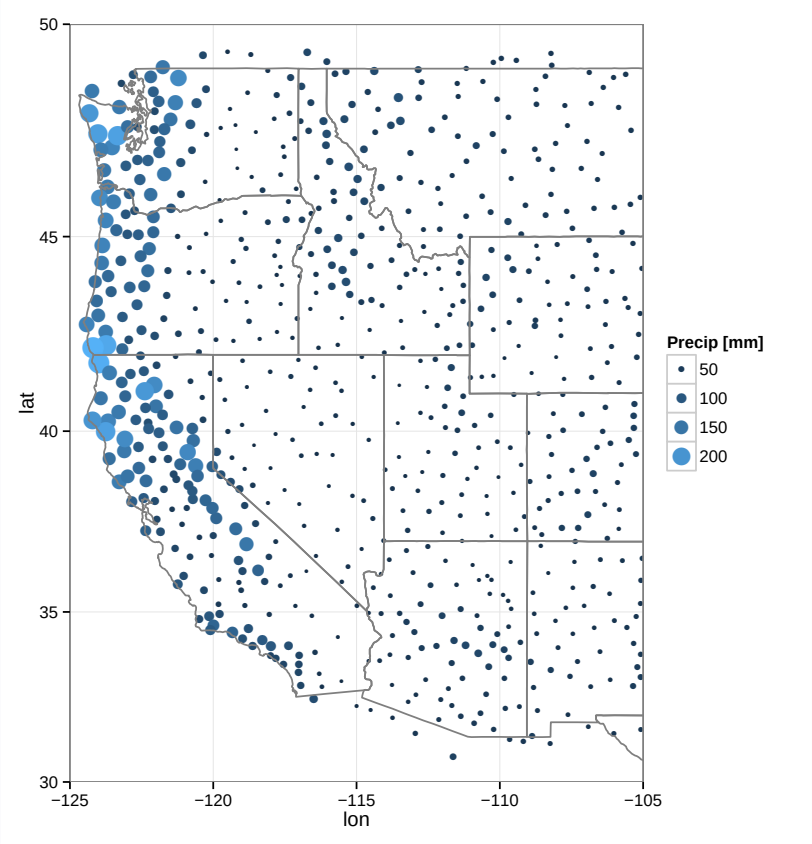
Precipitation
Maurer et. al. 2002, gridded product derived directly from observations, and both the land surface water and energy budgets aggregated to HUC8 basins in the western US (703 basins, 1949-2010).

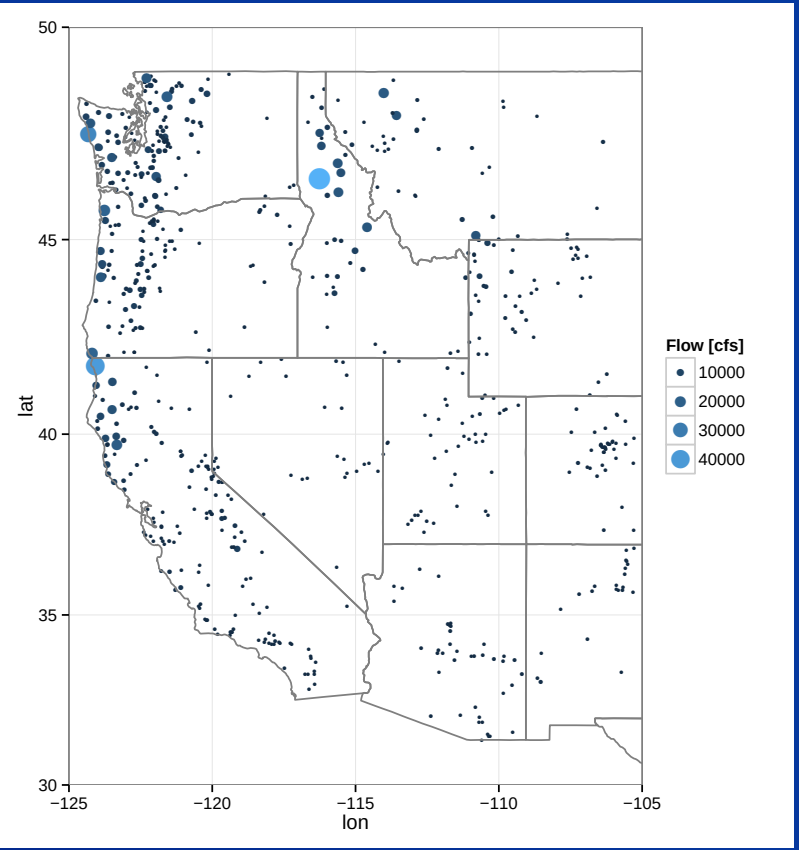
Data Preprocessing

- 1, 3, 5, 10 and 30 day aggregation window (mostly interested in 1-5 day max)
- Winter seasonal (November-March) block maxima approach

Diagnostics: Precip (left) and Flow (right)

Mean 3-day Seasonal (Nov-Mar) Max





Clustering of Maxima

Goal: Objectively determine spatially coherent regions over which extreme values behave similarly. (Later we will link these to the climate)

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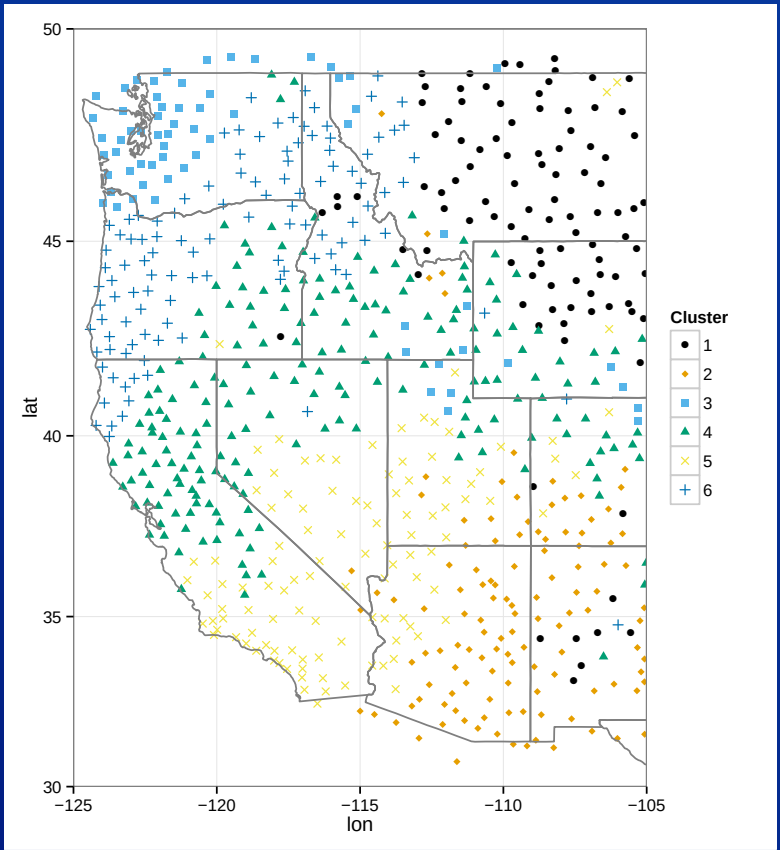
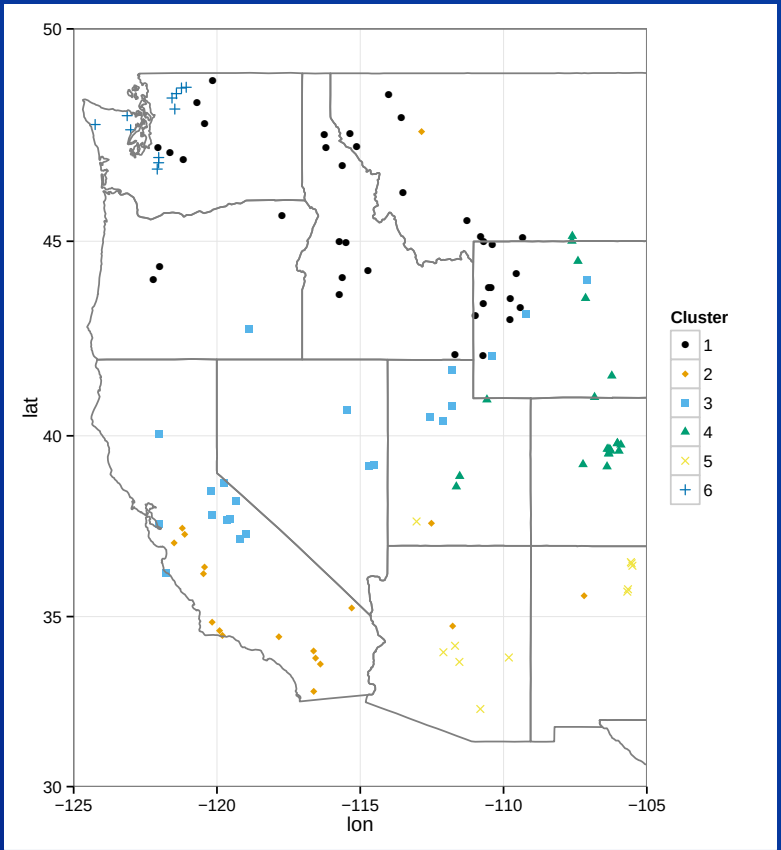
- **Solution 2**: Dissimilarity matrix based on the F-Madogram (non-parametic, based on shape of empirical CDF) (Bernard et al. 2013).

Clustering: 5-day Seasonal (Nov-Mar) Max.

Precip



Flow (120 locations)

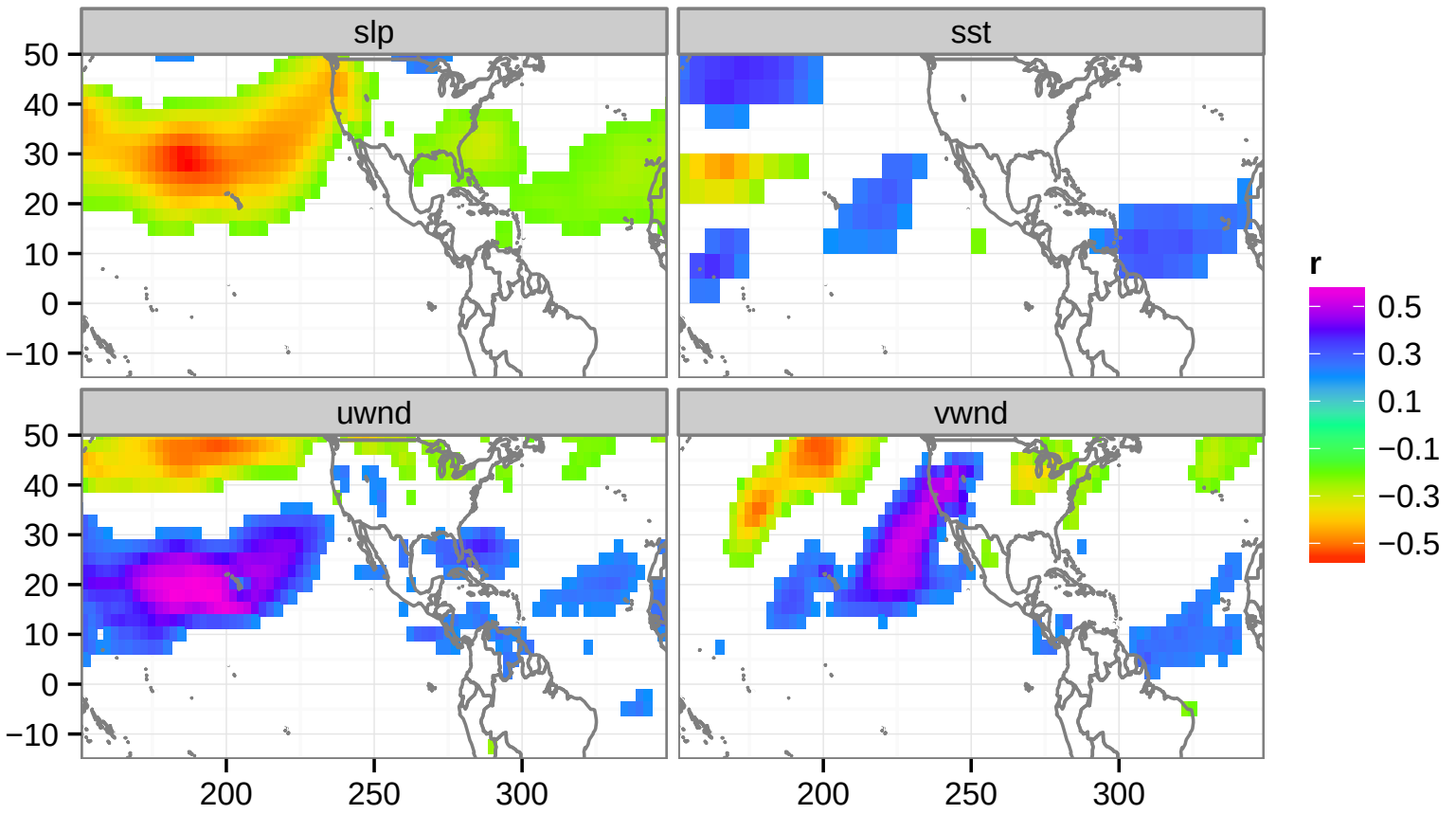


- No spatial information used
- Choice of number of clusters can subjective.

Climate Covariates - Precip

What large scale climate variables are linked to extreme value behavior in each cluster?

Cluster 4 example:



Stationary Extreme Value Analysis

Procedure

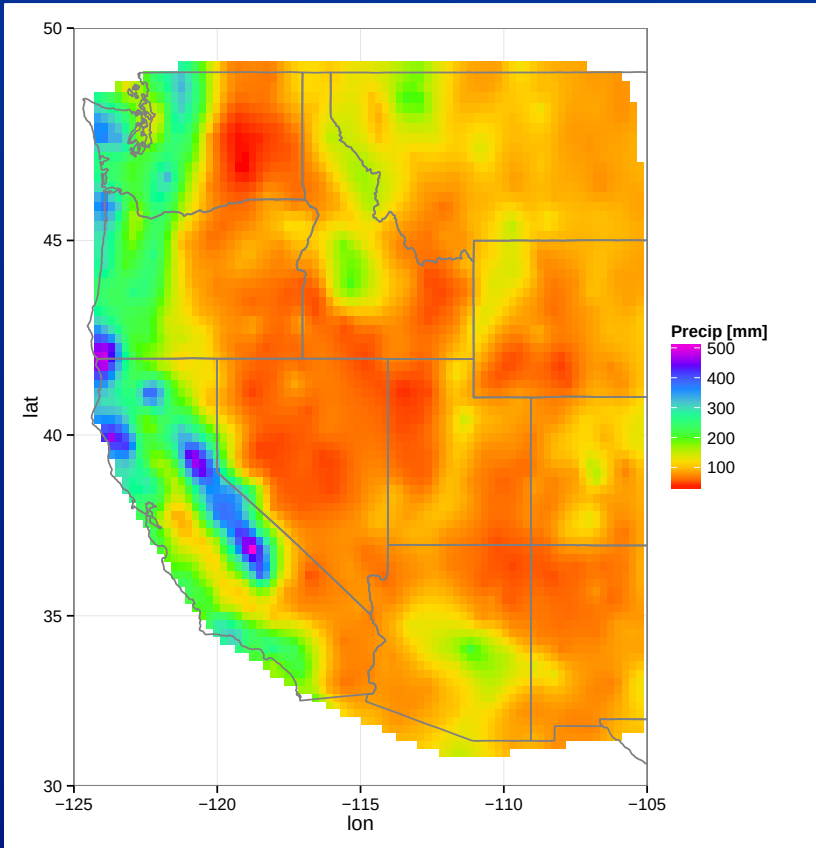
1. Fit a GEV distribution at each spatial location (CDF):

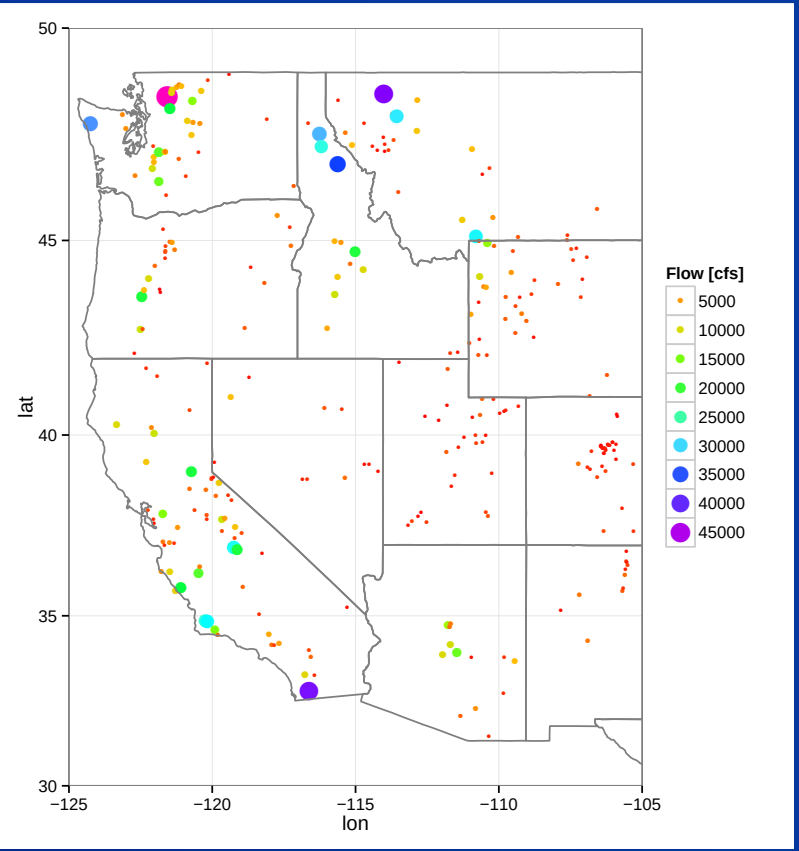
$$GEV(x;\mu,\sigma,\xi) = \exp\left\{-\left[1+\xi\left(\frac{x-\mu}{\sigma}\right)\right]^{-1/\xi}\right\}$$

2. Smooth the parameters in space (with a kriging model)
3. How is this useful?
   - Return period maps at locations with no data.
   - No need for a separate spatial model for each return period.

Stationary Extreme Value Analysis

3 day seasonal 100 year return period maps of Precip (left) and Flow (right).





Nonstationary Extreme Value Analysis

What if the parameters of our GEV distribution are changing in time (i.e. climate change)? We can use climate covariates (z) to estimate long term trends.

$$\mu(z) = \mu_0 + \mu_1 z$$

$$\log \sigma(z) = \sigma_0 + \sigma_1 z$$

$$\xi(z) = \xi$$

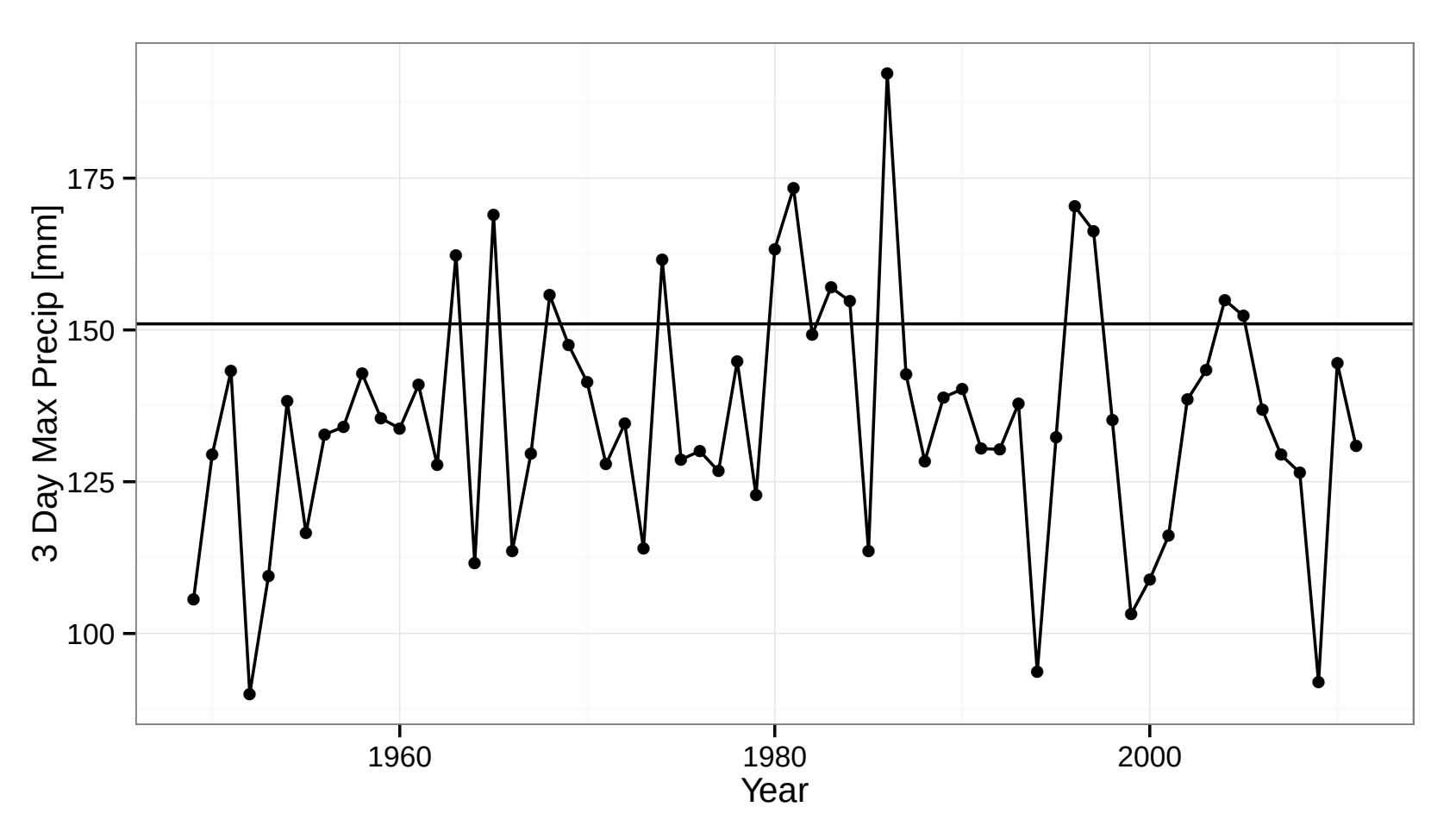
Nonstationary Extreme Value Analysis

Procedure:

1. Identify climate covariates (for each cluster, use first PC) based on regions of high correlation with climate variables
2. Fit a nonstationary GEV model for each cluster.
3. Return period map for each year
4. Ability to project into the future.

Nonstationary Extreme Value Analysis

Example Nonstationary 100 year return period, HUC 18010202



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Summary

1. Side by side analysis of extreme precipitation and streamflow over the western US
2. Extreme value oriented clustering for identification of spatial coherence of extremes
3. Stationary and nonstationary spatial extreme value models for flood frequency analysis

Conclusions and Lessons Learned

- Spatial coherence of extremes appears to exist in the western US (on this particular scale)
- Climate covariates that give insight into physical mechanisms that generate extreme event

Next Steps/Future Work

- Additional climate variables
- New datasets (perhaps raw data)
- Spatial extremes model (max stable process)
- Implications for infrastructure planning